Title

Online learning and Human Capital development in Africa: Harnessing the digital and demographic dividends

Author
Tadesse, Azeb

Publication Date
2023

UNIVERSITY OF CALIFORNIA

Los Angeles

Online learning and Human Capital development in Africa:

Harnessing the digital and demographic dividends

A dissertation submitted in partial satisfaction of the

Requirements for the degree Doctor of Philosophy

in Education

by

Azeb Tadesse

2023

ABSTRACT OF THE DISSERTATION

Online learning and Human Capital development in Africa:
Harnessing the digital and demographic dividends

by

Azeb Tadesse

Doctor of Philosophy in Education

University of California, Los Angeles 2023

Professor Walter Allen, Co-Chair

Professor Claudia Mitchell-Kernan, Co-Chair

The convergence of a digital transformation and a growing youth population in Africa represents an opportunity to harness digital and demographic dividends to boost human capital development. Higher education institutions play a central role in this process as the demographic dividend is accrued from the rise in the proportion of educated individuals rather than simply from an increase in population. Moreover, digital transformation has significant implications for education and the workplace, presenting higher education institutions with the challenge of increasing enrollment and integrating digital training while contending with infrastructure and personnel constraints.

Leveraging online learning offers a mechanism for overcoming physical limitations and staffing shortages to meet the challenge of providing educational opportunities to a growing pool of eligible applicants. However, whether online learning can deliver higher or equivalent

learning outcomes than face-to-face instruction is a factor in determining its practicality as a supplement to campus-based instruction. Therefore, evaluating the suitability of online learning requires an empirical assessment of its efficacy and a study of the factors that influence its deployment in established higher education institutions.

The sequential mixed-method study examined the efficacy of online learning at the University of Ghana (UG) and Addis Ababa University (AAU). The quantitative method examined whether online instruction had a causal effect on learning outcomes as measured by Cumulative Grade Point Average (CGPA). A propensity score matching analysis shows online learning had outperformed face-to-face instruction in UG by 9.28% ($p=0.045$) and AAU by 20.7% ($p=0.001$). The qualitative case study of AAU and UG documented the evolution, location, and implementation of online learning and the institutional and individual challenges in its deployment. UG and AAU have developed complementary strengths in the deployment of online learning. AAU's strength lies in providing sophisticated technical infrastructure and support for effective technical deployment, whereas UG has developed a process and mechanism to monitor the quality of online courses. The study found UG and AAU demonstrate an asset-based strategy for deploying online learning by leveraging strengths and developing solutions unique to their context, illustrating the importance of adaptation and indigenization in the deployment of online learning.

This dissertation of Azeb Tadesse is approved.

Ozan Jaquette
Cecilia Rios Aguilar
Tasse Abye
Walter R. Allen, Committee Co-Chair
Claudia Mitchell-Kernan, Committee Co-Chair

University of California, Los Angeles

2023

DEDICATION

In loving memory of

my father, Tadesse Lemma, and my mother, Abeba Gebremichael,

who lovingly supported and nurtured me,

helping to shape me into the person I am today,

and on whose shoulders I stand.

TABLE OF CONTENTS

ABSTRACT OF THE DISSERTATION ..... **ii**
COMMITTEE PAGE ..... **iv**
DEDICATION ..... **v**
TABLE OF CONTENTS ..... **vi**
LIST OF TABLES ..... **ix**
LIST OF FIGURES ..... **x**
LIST OF ACRONYMS ..... **xi**
ACKNOWLEDGEMENTS ..... **xiii**
VITA ..... **xv**
CHAPTER 1 | Introduction **1**
Introduction 1
Background 3
Problem Statement 9
Research Question 9
Context 9
Organization of dissertation 14
Significance of study 15
CHAPTER 2 | Literature Review **17**
Introduction 17
Extant Literature 18
Knowledge, learning and the university 18
Higher education in Africa 19
Demographic dividend 27
Demographic dividend and gender 31
Online learning 33
Online learning and gender 43
Low connectivity 45
Technology and the gender digital divide 50
Summary 53
CHAPTER 3 | Conceptual Framework **55**
Introduction 55
Human capital 56

Physical capital vs. human capital 56
Human Capital Theory 58
Human capital and gender 73
Conceptual framework 77
Human capital for the twenty-first century 77
Summary 82
CHAPTER 4 | Methodology 84
Introduction 84
Study Sites 84
Research question 87
Research design 88
Quantitative 89
Quantitative study sample 90
Quantitative data collection 91
Quantitative data analysis 97
Limitations 115
Qualitative 117
Qualitative case study 117
Qualitative data sample 118
Qualitative study instruments 119
Qualitative data analysis 120
Summary 121
CHAPTER 5 | Quantitative Analysis 123
Introduction 123
Descriptive statistics 124
University of Ghana – Study Variables 124
Gender 130
Addis Ababa University Study variables 132
Gender 135
Propensity score matching 137
University of Ghana 137
Addis Ababa University 139
Summary 140
CHAPTER 6 | Qualitative Analysis 142

Introduction 142
University of Ghana 143
Addis Ababa University 152
Summary 159
CHAPTER 7 | Discussion 161
Introduction 161
Study findings 161
Online vs. face-to-face instruction 161
Impact of historical legacy 166
Implications for practice 173
South-South Cooperation 174
Data management 175
Digital technology deployment 176
Recommendations for future research 176
Conclusion 177
APPENDICES 185
Appendix I – Development indicators
Appendix II – Profile of Study Sites
Appendix III – Population Pyramids
Appendix IV Connectivity map
Appendix V – Campuses and Learning Centers
Appendix VI – UG and AAU quantitative analysis
Appendix VII – Qualitative questions

REFERENCE 380

LIST OF TABLES

Table 1: Government Expenditure and Enrollment Ratio 25

Table 2: Study Notation 101

Table 3: Procedure for Matching Using *Matchit()* 114

Table 4: Estimated Effect of UG and AAU 139

LIST OF FIGURES

Figure 1: Population Pyramid of Africa 2050 2

Figure 2: Ghana and Ethiopia 12-24 Population Projection To 2050 28

Figure 3: Submarine and Terrestrial Map Of Africa 46

Figure 4: Conceptual Framework 79

Figure 5: Campuses and Learning Centers 87

Figure 6: Propensity Score Matching 113

Figure 7: UG Enrollment 127

Figure 8: Addis Ababa University Enrollment 133

Figure 9: Gender Distribution of CGPA and Age 136

Figure 10: Covariate Balance Across Subclass UG and AAU 138

LIST OF ACRONYMS

AAU	Addis Ababa University
AI	Artificial Intelligence
ARE	Average Treatment Effect
ATET	Average Treatment Effect on Treated
CGPA	Cumulative Grade Point Average
CIA	Conditional Independence Assumption
DDE	Department of Distance Learning
EdTech	Educational Technology
GCI	Global Connectivity Index
GDP	Goss Domestics Product
GER	Gross Enrollment Ratio
GPI	Gender Parity Index
HEI	Higher Education Institution
IBRD	International Bank for Reconstruction and Development
ICT	Information and Communication Technology
IDE	Integrated Development Environment
IMF	International Monetary fund
IRB	Institutional Review Board
LMS	Learning Management System
LTE	Long-Term Evolution
MAR	Missing at random
MCAR	Missing Completely At Random

MOOCs	Massive Open Online Courses
NBER	National Bureau of Economic Research
NEET	Not in Employment, Education or Training
OLS	Ordinary Least Squares
PSM	Propensity Score Matching
SAP	Structural Adjustment Program
SHS	Senior High School
SSC	South-South Cooperation (SSC)
SSL	Secure Sockets Layer
SSR	Sum of Squared Residuals
STEM	Science, Technology, Engineering, and Mathematics
SUTV	Stable Unit Treatment Value
TLS	Transport Layer Security
UG	University of Ghana
UNISA	University of South Africa
USAID	United Stated Agency for International Development
UTE	Unit Treatment Effect

ACKNOWLEDGEMENTS

This journey would not have been possible without the love and support of my family Tenagne Tadesse, Henok Tadesse, Jarra Keskessa, Portia Tadesse, who picked up the load when I couldn't be there, and the heart and soul of our family Ethan Tadesse Keskessa. My family, who has always stepped in to support me, Genet Lemma and Girma Debele. And Dr. Solomon Hailmariam, our family's advocate and sounding board for research and exploration.

I would not have contemplated returning to UCLA for this research and degree without the mentorship and support of my co-mentors, Dr. Walter Allen and Dr. Claudia Mitchell-Kernan. I want to thank Dr. Allen for making a place for me among the brilliant scholars he mentors, encouraging my intellectual curiosity, and offering a platform for exchanging ideas. Dr. Mitchell-Kernan for her steadfast commitment to my personal and professional development and her mentorship and friendship spanning continents. Dr. Edmund Keller for mentoring me through my undergraduate and graduate degrees, my first job, and for the constant personal and professional support and friendship.

I am fortunate to have had a committee of thoughtful, kind, and dedicated scholars who supported my work and were always available to me on this journey. I want to thank my committee for the rich intellectual dialogue and discourse they generously provided that deepened my work, Dr. Ozan Jaquette for demonstrating data can be a social justice tool, Dr. Cecilia Rios-Aguilar for humanizing economics and technology, and Dr. Abye Tasse for probing so much of what we take for granted when studying Africa, especially in the context of higher education.

My field research would not have been possible without the support of the UCLA Bunche Center/Institute for American Cultures Research Grant Program, the US Department of

Education Fulbright-Hays Doctoral Dissertation Abroad Fellowship, and Mr. and Mrs. Haskell Sears Ward.

I'm grateful for the collaboration and collegial welcome of the University of Ghana School, School of Continuing and Distance Education, including Dr. John Boatang (Senior Lecturer), Dr. Samuel Amponsah (Head of the Distance Education Department), and Dr. Olivia Frimpong Kwapong (Dean of the School of Continuing and Distance Education) and the many faculty and students at the university who supported my work through interviews and discussions. My work in Ghana was enriched by the support of Jennifer Green and the Public Affairs Section of the US Embassy in Ghana, who created a welcoming family for Fulbrighters, Edmund Aalongdong, Seble Kagnew, Grace Aynsue and the many friends who formed my village.

I was able to continue my research at Addis Ababa University despite COVID and other closures through the support of Dr. Abiy Zegeny (AAU), who took on the task of scheduling interviews and meetings, and Dr. Solomon Hailemariam (Ethiopian Academy of Sciences), without whose support my research in Ethiopia would not have been possible.

VITA

Master of Arts Education University of California, Los Angeles, CA
Master of Arts African Studies, University of California, Los Angeles, CA
Master Thesis: Ethiopia: Politicized Ethnicity and Its Implications on Development and Democracy
Bachelor of Arts History, University of California, Los Angeles, CA

EMPLOYMENT
Senior Operations Officer, International Finance Corporation/The World Bank Group
Deputy Director, UCLA International Institute, African Studies Center
Assistant Director, UCLA International Institute, African Studies Center, Los Angeles, CA

PUBLICATION
Tadesse, A., Damacio, B., Billot-Vasquez, K., and Allen, W. R. (2023) *Issues of Production and Utilization of Knowledge: Multiple uses of knowledge*, Encyclopedia on Education. Elsevievier.

Williams, B., Bitar, J., Polk, P., Nguyen, A., Montague, G., Gillispie, C., Waller, A., Tadesse, A., and Elliott, K. C. (2022). "For Student Parents, The Biggest Hurdles to A Higher Education are Costs and Finding Child Care". The Education Trust https://edtrust.org/resource/for-student-parents-the-biggest-hurdles-to-a-higher-education-are-costs-and-finding-child-care/

Monet Reynoso, N., Tadesse, A., Foxx, K., Mack, C. (2022). *Patching the Pipeline: Reimagining the Roadmap to Higher Education.* In African American Leadership and Mentoring Through Purpose, Preparation, and Preceptors.

Tadesse, A., Allen, W., Mitchell-Kernan, C. (2021) *Integrating Educational Technology in East Africa: One Size Does Not Fit All.* Monitoring of Public Opinion: Economic and Social Changes. No 1 (161) Jan-Feb 2021.

Opinion
Tadesse, A. and Aalangdong, E. (2022). *Can online learning increase access and the instructional capacity of African higher education intuitions?*, Africa Up Close, The Wilson Center https://bit.ly/africanonlinelearning

Conference
Oxford Education Research Symposium (December 2022)
Online learning in African higher education: The case of the University of Ghana and University of Cape Coast

AWARDS
Fulbright-Hays Doctoral Dissertation Research Abroad, 2021
UCLA Graduate Mentorship Summer Research, 2021
Bunche Center for African American Studies Research Grant, 2020
Institute for American Cultures Research Grant, 2020
UCLA Excellence in Leadership (Excel) Award, 2013

CHAPTER 1 | Introduction

Introduction

Traditional development theory holds there are steps a country must take to become what is commonly referred to as a developed nation. These stages are broadly defined as a society progressing from an agrarian economy to one focused on manufacturing, then industrialization, and finally, a technology-based economy (Diebolt & Hippe, 2019; W. A. Lewis, 2003; Lonska & Mietule, 2015; Omar, 2012). However, technological advancements have enabled countries to bypass certain steps and phases, rendering the traditional theory of development progression obsolete. This stage-skipping is known as leapfrogging "when a nation bypasses traditional stages of development to either jump directly to the latest technologies (stage-skipping) or explore an alternative path of technological development involving emerging technologies with new benefits and new opportunities (path-creating)" (Yayboke, 2020). Mobile technology, for example, has increased phone, internet, and banking access while removing the need for costly infrastructure such as landlines. Similarly, digital technology[1] in the workplace has led to stage-skipping, with old jobs like switchboard operators and travel agents disappearing and new ones like software designers and social media managers emerging.

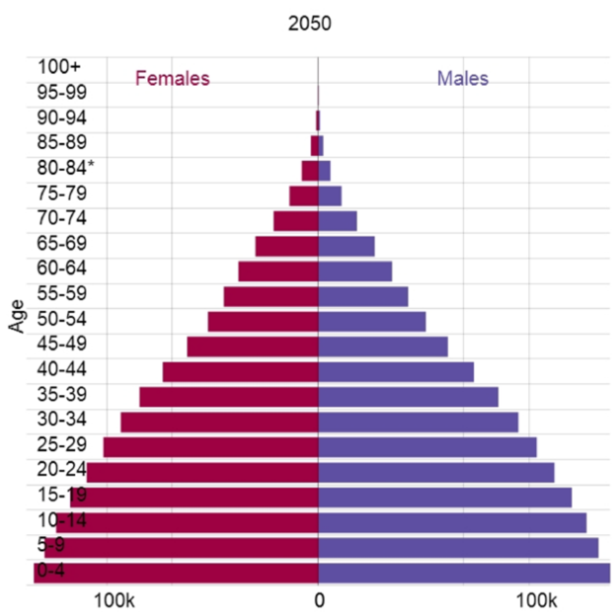
The expansion of digital technology, defined by the adoption and use of technology, introduced far-reaching transformations that continue to redefine society and culture. For instance, the digital transformation in the workplace has been dramatic, rapidly changing the skills required for employment, from tasks to job functions. This global disruption extends to

[1] In the context of this study, digital technology is defined as "a wide range of technologies, tools, and applications using various types of hardware and software…to facilitate services or activities by electronic means to create, store, process, transmit, and display information..[it] includes the use of personal computers, digital television, radio, mobile phones, robots, etc." (Tulinayo et al., 2018, p. 1)

Africa, where the demand for digital skills is growing faster than in any other region, with an estimated 30 million jobs requiring digital skills by 2030 (IFC/The World Bank, 2019).

Thus, this digital transformation has implications for the skills needed in today's workforce, presenting HEIs with the "unprecedented challenge of updating education systems built for another era" (IFC/The World Bank, 2019). Meanwhile, Africa's population age structure is changing dramatically, where the continent will account for more than half of the projected global population growth from now to 2050, with 60% of the population under the age of 25 in 2017 expected to increase to 1.2 billion by 2050 (United Nations, 2017) *(see Figure 1).* Therefore, the recent surge in demand for access to training in digital skills is fueled by this trifecta of globalization, digital transformation, and the youth bulge.[2]

Figure 1: Population Pyramid of Africa 2050



[2] Youth bulge is "[t]he relatively large increase in the numbers and proportion of a country's population of youthful age, conventionally 16–25 or 16–30. When infant mortality rates fall but fertility rates do not, at least in the short term, there will be a surge in the number of births relative to preceding years. As this cohort ages it enters the age at which waged employment is the norm. If economic conditions are favourable, as they were in much of East Asia, the result is a 'demographic dividend', an expansion of labour that contributes to economic growth. But under less favourable conditions, a 'demographic bomb' can result in young people being unable to find employment. It has been argued that this is one factor behind youth political unrest, notably in North Africa and the Middle East in 2011" (Rogers et al., 2013)

This convergence of digital transformation and a growing youth population also affords Africa the potential to accelerate human capital[3] development by focusing on "how technology interacts with other factors that are important for development" to harness digital and demographic dividends (The World Bank, 2016, p. 4). For most African countries, these development factors are the youth bulge and education. The path to maximizing the digital and demographic dividends lies in harnessing the digital dividend to "leapfrog" physical and infrastructure constraints to build and expand learning and skilling spaces that allow the youth population to access the education and skills needed for participation in the information and knowledge economy, thereby fueling the demographic dividend.

Therefore, Africa's path to economic growth rests in the appropriate deployment of educational technology to prepare students for employment and self-employment in an increasingly globalized, digital world. The increasing rate of digital instructional innovation represents an opportunity to address the persistent and long-standing capacity challenges African higher education institutions (HEIs) face. Online learning is one such innovation that uses technology to create virtual classrooms and is a vital element of the education-technology nexus.

Background

The challenge African HEIs face stems from the unprecedented increase in qualified candidates seeking placement as a result of improvements in human capital investments in health and education. This increase resulted from decades of investment that reduced infant mortality, increased the population's general health, and improved primary and secondary education, thus setting the stage for a demographic dividend (S. A. Ahmed et al., 2014). The key to realizing the

[3] In the context of this study human capital is defined as "the skills, knowledge, and qualifications of a person, group, or workforce considered as economic assets" (Marriam-Webster.com Dictionary, 2023).

benefits from the demographic dividend lies in the increase in the number of educated individuals participating in the economy rather than simply increasing in the population (S. A. Ahmed et al., 2014; Drummond et al., 2014; Lutza et al., 2019; Renteria et al., 2016). For example, in the late 1900s, the rapid growth of the Asian Tigers, Hong Kong, Singapore, South Korea, and Taiwan, was not primarily driven by an increased youth population. The Tigers capitalized on the demographic transition by increasing human capital investment through a focused, intensified investment at all levels of the education cycle and targeted technological integration, yielding a dividend of up to 25% to their economic growth (IMF, 1994; Pack & Nelson, 1999; V. V. Bhanoji Rao, 1999). Therefore, harnessing the demographic dividend is simply not a function of increasing the working age population but requires active investment in human capital accelerators, such as education, to enable young workers to lead fulfilled lives and participate in the economy.

Moreover, workplace disruptions by the digital transformation have shifted education and training where "not only have new demands for trained manpower emerged, but new forms of training that meet the expectations of the new economy are now expected from higher education institutions" (Nampala et al. 2017, p. 145). Existing education and training have proven to be incompatible with the technological age and the knowledge economy, resulting in considerable skills mismatch[4] "driven not only by low-quality education but also demographic change, rapid technological development, new sources of job creation and new forms of work organization" (ILO, 2019, p. v). Although this is a global challenge, Africa has the highest rate of skills

[4] Skills mismatch is when "[s]kills (qualifications) mismatch corresponds to a misalignment between the skills (qualifications) demanded in the labour market and the skills (qualifications) possessed by the labour force. It arises, in particular, when the education system fails to supply the skills sought by employers (supply side), or when the economy fails to create jobs that correspond to individuals' skill endowments (demand side)" (UNESCO IIEP, 2022)

mismatch, where young workers cannot secure employment, regardless of their level of education. According to a recent Ghanaian survey of youth aged 18 to 35, 44% cited unemployment and 38% education as the most critical issues the government must address (Appiah-Nyamekye Sanny, 2020). Moreover, unemployment and lack of educational opportunities are frequently cited as push factors for legal and illegal migration out of Africa, which has grown by 50% from 2010-2017, with Ghana and Ethiopia ranking among the top four countries (Pew Research Center, 2018a).

As a result of this chronic skills mismatch, underemployment, low-quality jobs, and vulnerable employment are standard features of the African labor market and a causative factor of social and economic disruption. Although empirical research on skills mismatch is still in its early stages, a few indicators, such as labor underutilization,[5] provide insights into the dynamics. Africa's underutilization is estimated to be more than 20% of the global average, indicating a significant mismatch between the labor supply and workplace demand, leading to unemployment and underemployment. Moreover, several studies on youth unemployment in Africa caution the continent's reported low youth unemployment rate masks a significant disconnect between education and the labor market. This assessment is supported by disaggregated unemployment data, which shows a higher unemployment rate among those with education.

While youth unemployment in Africa is generally reported to be between 5% and 6%, this figure does not consider the need for people need to earn a living, and they simply cannot afford to wait for the right job, so they end up in insecure and low paying jobs (UNESCO, 2022). Hence, the youth unemployment rate does not measure job quality but simply indicates a person

[5] "Labour underutilization refers to mismatches between labour supply and demand, which translate into an unmet need for employment among the population. Measures of labour underutilization include time-related underemployment, unemployment, and the potential labour force. Other dimensions of underutilization of labour at the level of individuals as well as the economy are skills mismatches and slack work" (ILO, 2023).

has a job, regardless of its quality and fit. In Ghana, for example, the overall unemployment rate was 3.4% in 2017 and 6.2% for those aged 15 to 24 (ILOSTAT, 2023b). Additionally, the inactivity rate in Ghana for workers 15-64 in 2017 was 28.7%. Of the inactive workers, those with less than basic education account for 21.6%, t with basic education 24%, intermediate education 38.5%, and advanced education 33.2% (ILOSTAT, 2023a). However, the inactivity rate for youth 15 to 24 nearly doubles to 53.6%, while those with less than basic education remains constant at 25.2%. For intermediate education, the rate almost doubled to 59.9%, and for advanced education, the rate more than doubled to 78.8% (ILOSTAT, 2023a). Furthermore, in the same year, the proportion of youth (15-24) not in employment, education or training (NEET) in Ghana was higher in urban areas, 27.2%, than in rural areas (18.5%) (ILOSTAT, 2023c). These indicators show a concentration of unemployment among those with education and suggest the rate of worker inactivity rises as the educational attainment level increases, implying a negative relationship between education and employment.

This relationship between education and employment and the prevailing skills mismatch suggests HEIs produce graduates who lack the prerequisite skills and training for employment. This training gap reflects the state of HEIs as they recover from decades of neglect, which has resulted in capacity deterioration, infrastructure deficits, faculty brain drain, and overcrowding (Jowi et al., 2013). The employment challenges mentioned above are manifestations of HEIs' acute underfunding and marginalization, which has resulted in an inability to admit qualified applicants, graduate unemployment exceeding 50%, and a severe disconnect between institutions, society, and the economy in which they operate. These issues have implications for HEIs, where capacity and infrastructure gaps create obstacles in harnessing the digital and demographic dividend. Therefore, HEIs must address a plethora of complex and diverse issues to meet the demands of educating and training a growing youth population in both the theoretical and practical knowledge and skills required to live meaningful lives and find gainful employment in the digital age.

African HEIs are expected to develop and deliver training and education for the digital age while dealing with a shrinking pool of qualified candidates for faculty positions to keep up with increasing enrollments. Faculty are unable to customize and update courses regularly, provide academic and career guidance, track student progress, address absenteeism, and provide additional support due to teaching overload and classroom overcrowding. Consequently, graduates leave with “minimal learning and limited skills for work” (Kokutse, 2020). Whilst also dealing with these deficits, HEIs are under increasing pressure to keep up with labor market changes, as evidenced by “growing employer complaints that graduates are poorly prepared for the workplace” of the digital economy based on knowledge and technology (Materu, 2007). On the other hand, the demands placed on HEIs are unfunded mandates. There are few options for addressing access and training in an environment of declining public spending and inadequate funding models, especially since additional infrastructure and increased hiring are unrealistic due to time and budget constraints.

Yet, harnessing the digital and demographic dividends requires fundamental changes in education and training, including a strengthened skills agenda and innovative strategies to deliver the right combination of foundational, technical, digital, and socio-emotional skills to an increasing number of students. Meeting the challenge of a changing job landscape that requires new skill sets, along with managing rising enrollment caused by a youth bulge, is a massive undertaking. Expanding capacity through additional facilities and instructors is prohibitively expensive and time-consuming as the number of qualified candidates grows; however, educational technology can potentially augment educational access (Altbach et al., 2009). Leveraging the digital transformation to deploy online learning offers a mechanism to bypass physical limitations and staff shortages to meet the challenge of providing educational opportunities to the growing pool of qualified applicants.

Though there has been some ambiguity and disconnect in the use of technology in higher education, it is present in all aspects, from collaboration to publishing to research (Altbach et al., 2009). Incorporating technology into instruction has the potential to broaden the reach of educational programs. Online learning leverages advancements and innovations in technology to support, supplement, customize, personalize, and diversify instruction. Supplementing and complementing instructional delivery through the adoption of online learning can potentially increase enrollment and program offerings to meet the growing demand for educational access and relevance.

The Covid19 pandemic has demonstrated the ability of educational institutions to adopt technology at an accelerated pace and the pitfalls of indiscriminate adoption of educational technology (Assié-Lumumba, 2008). In a report by eLearning Africa (2020), 85% of online learning experts across the continent anticipated a continued widespread use of technology in education due to the extensive use of remote instruction during the Covid-19 pandemic. However, the report also cautioned that the deployment of technology would pose "significant challenges for the most marginalized and may increase inequality" (eLearning Africa, 2020). Therefore, African HEIs must be deliberate and innovative in determining which technology best fits the environment and accommodates students' limitations.

Problem Statement

African HEIs are endeavoring to meet the increased demand for digital skills training, driven by the rapid pace of globalization, digital innovation, and an increase in the youth population. Online learning is an additional tool for achieving this goal as it provides an opportunity to close capacity gaps in countries such as Ghana and Ethiopia, where expanding educational access is constrained by physical facilities and staffing. Virtual classrooms powered by digital technology have the potential to reduce enrollment constraints and alleviate the limitations that students face when pursuing education and training. However, the ability of online learning to deliver equivalent or improved learning outcomes is a critical factor to consider when deciding whether online learning is a feasible alternative to supplement campus-based instruction. As a result, evaluating the suitability of online learning requires an empirical assessment of its efficacy and a study of the factors that influence its implementation in established HEIs.

Research Question

To that end, the study will examine the effectiveness of online learning at the University of Ghana (UG) and Addis Ababa University (AAU) to interrogate the following research questions:

Research question 1: Is online instruction as effective as face-to-face instruction measured by Cumulative Grade Point Average (CGPA)?

Research question 2: How does the deployment and implementation of online learning in AAU and UG influence learning outcomes?

Context

The study covers a wide range of topics that, while seemingly unrelated, are inextricably linked and require a critical lens. Critical theory emphasizes “social facts not as inevitable constraints on human freedom but pieces of history that can be changed” (Agger, 1991, p. 109).

Thus, it is essential to deconstruct terms like development and knowledge, as well as interrogate the nature and character of institutions, to “identify oppressive structures [and] hegemonic power dynamics” and engage in a “dialectical imagination” that critiques and challenges power structures.

Defining knowledge, education, and the very concept of the university enters the spaces of power, epistemology, and the enduring legacy of colonialism. Thus, we ought to note knowledge is inextricably linked to power, defined as the ability to generate it, propagate it, and institutionalize it (Foucault, 1980). Knowledge can be generated anywhere by anyone, however, the nexus of power relations serve as arbiters in order to preserve their authority by determining what is accepted as the ‘truth’ (Foucault, 1980). Thus, the interaction between power and knowledge has molded our understanding of what constitutes legitimate knowledge generation and transmission, a concept filtered and interpreted in service of the status quo. Hence, the generation and transmission of knowledge are ultimately linked to the interplay of what Foucault referred to as power/ knowledge. According to Foucault, power is reinforced and sustained by the acquiescence to certain forms of knowledge and truths (Rainbow, 1991). Therefore, gatekeeping functions as a mechanism for legitimizing knowledge, isolating sources, methodologies, and platforms that do not conform to, and question, the established paradigm.

The nature of colonialism can be understood as a process where the knowledge base—the political, social, and cultural—of the colonized was violently interrupted, ceased to exist, to be replaced by a new system. Post-colonial scholar Boaventura de Sousa Santos (2014) defines colonialism as “a system of naturalizing differences in such a way that the hierarchies that justify domination and oppression are considered the product of the inferiority of certain peoples and not the cause of their so-called inferiority” (2014, p. 18). In addition to realigning global paradigms of power and legitimacy, colonialism was also complicit in what Sousa Santos calls epistemicide “the destruction of the knowledge and cultures of [oppressed] populations, of their memories and ancestral links and their manner of relating to others and to nature” (Santos, 2016, p. 18). As a result, colonialism was an exercise in the erasure and delegitimization of local systems, including knowledge systems, which were uprooted and replaced by hierarchical systems that were extrinsically defined with hardly any meaning to local realities.

The intrusion and encroachment of external systems inevitably create fragmentation, with individuals experiencing alienation and disconnectedness from their context. Franz Fanon (1963) described colonialism as a violent encounter defined by exploitation and marked by dehumanization, which served to deprive the oppressed of a sense of selfhood. This estrangement and dissociation from oneself are expressed as social, psychological, and cultural alienation, characterized by conformity, acceptance, and internalization of the colonizer’s social construct. Hence, the power to generate, validate, and legitimize knowledge and the truth regarding oneself and circumstance is transferred and conferred upon the colonizer, who inevitability becomes the standard and measure, a point of comparison, for one’s existence.

Despite the end of colonialism, the colonizer remains the standard and measure therefore, it is instructive to apply a critical lens to post-colonial international development. Even though international development employs a different approach, it nevertheless continues to impose external agendas that are disconnected from, irrelevant to, and in conflict with local realities and national priorities. International development is a collection of theories and practices on the development process that rely primarily on deeply problematic dichotomies that were used in the colonial era to legitimize oppression and exploitation (Zvobgo & Loken, 2020). The practice is premised on the idea that there is an objective and unbiased standard for what it means to be developed. This approach also assumes that industrialized countries' experiences and systems, independent of history or culture, are effective and suitable roadmaps for other regions.

What is generally known as international development took shape towards the end of WWII, centered around rebuilding Europe (USAID, 2019). While depicted as a philanthropic effort, development aid was established to create economic blocs at the end of WWII. In 1942, President Roosevelt was presented with a plan for a financial system that stabilized currencies and prevented a global depression like that of the 1930s (Asher & Mason, 1973). The plan was adopted during the meeting in Bretton Woods, establishing the International Monetary Fund (IMF) and the International Bank for Reconstruction and Development (IBRD), more commonly known as the World Bank (Oliver, 1996; USAID, 2019). Shortly after, in 1948, the Marshall Plan, a $15 billion project to rebuild Europe, was founded. The Marshall Plan was also the first large-scale international development project, but it was also a mechanism for shoring up support for Bretton Woods, IMF, and World Bank, economic policies (Asher & Mason, 1973; Oliver, 1996). While widely regarded as a charitable and humanitarian program, the Marshal Plan was designed to orient European nations to the new economic and monetary strategy. After the post-war period, international development spread to other parts of the world, including former European colonies.

Sixty years after the Marshal Plan, international development is a primary organizing principle of international relations, deeply rooted in Western principles that define 'developed' (Asher & Mason, 1973). Omar (2012) points out the basic principle of development cooperation is "predicated on a predominant, persistent idea consisting in the desirability and need for developing underdeveloped areas and in the associated assumption that this development would be possible only with some assistance from or intervention by the developed world." In some ways, international development maintains past relationships, first by characterizing the Global South[6] as underdeveloped, and secondly, “development is framed by a distinct relationship between aid donors and recipients mapped onto a first world/third world or developed/ underdeveloped divide” (Kothari, 2006, p. 2). This framing highlights the enduring historical aspect of geopolitics and asymmetrical power. Thus, the primary difference between colonialism and development is compliance is now enforced through development aid and loans rather than military force.

This framing of development as a benefit to the recipients of development aid has been challenged through dependency theory as early as the 1960s (W. A. Lewis, 2003; Rodney, 1972). Originating in Latin America and The Caribbeans but quickly spreading globally, the theory argued the primary framing of global systems had been domination-subordination, which in the current era is expressed as anchored in capital accumulation and the division of labor between the center and the periphery. The theory identified development as a process that was increasing inequality rather than correcting it because markets placed a higher value on finished products produced by the center than on the raw materials from the periphery (Rodney, 1972). This imbalance led to greater productivity and increased manufacturing and technical expertise in the center, prompting education and skills training and economic growth, while the periphery faced pressures to increase labor supplies, which focused on unskilled workers, thus deemphasizing human capital investment (W. A. Lewis, 2003). Therefore, development cannot break this

[6] In this study, the term "Global South" is defined as “a process or practice through which new modes of knowledge production are created and established modes of reproducing inequalities, “epistemicide” (Sousa Santos 2014)..are unlearned…[it is] an active practice that restructures global networks of power….a liminal space of transition in which a phase of anti-structure enables the re-organization of, social and epistemological power relations, and which creates a new model of social, economic, and political interactions that relies on egalitarian principles” (Sinah Theres Kloß, 2017, p. 8).

international division of labor where the periphery remains a source of resources transferred to the center, which only serves to grow the center's economy.

The dependency theory critique of development cooperation focuses on development's specific role as a mechanism for reproducing the unequal and exploitative relationship between the 'developed' and the 'developing' world, which in many cases are former colonies of the very patrons of development aid (Ferraro, 2008; Rodney, 1972). Dependency theory proponents argue economic growth was not beneficial to all, but rather prosperous economies developed at the expense of poorer ones. Developing countries grew their economies using the global economic model, namely the Bretton Woods Institutions, to force other nations to provide raw materials and markets for finished goods.

The preceding discussion not only defines key concepts and terms but also demonstrates the interconnectedness of an international system that underpins many of the issues raised in this study. The international system serves as the foundation for international relations and the terms of engagement among a global network of nations and organizations. It is critical to interrogate the framework of relationships that serves as the foundation of the system that determines the nature, context, and rules of that engagement. Especially when the relationship has been adverse, it is necessary to bring a critical lens to "look beyond the appearance of given social facts towards...new social facts" that will result in transformation and equity.(Agger, 1991, p. 109).

Organization of dissertation

The remaining part of the dissertation is organized as follows. Chapter 2 is a review of the available literature on several study related concepts. The chapter begins with an exploration of knowledge generation and early learning centers, then moves on to a discussion of higher education in Africa. The review concludes with a discussion of the demographic dividend and its relationship to education, followed by online learning and the challenges of low connectivity. The study's conceptual framework is presented in Chapter 3, which begins with early theories of human capital development, such as Adam Smith, discusses significant points in history where the theory was further developed, concludes with a strategy of human capital for the twenty-first century that serves as a framework for the study. The methodology chapter is Chapter 4, which introduces the research design, research questions, methodology, and data analysis. The quantitative study's data analysis and findings are discussed in Chapter 5, while the qualitative findings are presented in Chapter 6, with each institution discussed separately to highlight the study's sequential and dual case study features. Chapter 7 expands on research findings to discuss the significance of the findings and their implications for practice before concluding remarks.

Significance of study

Although remote learning has a long history in Africa, dating back to the establishment of the University of South Africa (UNISA) in 1946, online learning is a relatively new modality in much of Africa. Consequently, the opportunities to research and study the modality, process, and efficacy in Africa have not been abundant. This study investigates a relatively new area in which findings will add to knowledge building to inform practice in integrating online learning and potential drivers of the modality's deployment. Though there has been incremental growth in the data and information on online instruction in the African context, there are, nevertheless, areas that have yet to be considered. Recent studies on online instruction in Africa examined topics such as students' perceptions and opinions, student views incorporating e-learning, bibliometric analysis, and the impact of policy frameworks on delivery (Aalangdong, 2022; Asunka, 2008; Faturoti, 2022; Paschal & Mkulu, 2020; Simeon et al., 2022; M. Tagoe, 2012). However, there is a significant gap in the effectiveness of online learning and its potential for instruction in African HEIs.

Given the importance of increasing access to higher education in Africa, this study will investigate whether online learning has the potential to increase access to education for a growing pool of qualified applicants. It will also provide insight into the factors that influence the integration of online learning programs into established institutions, particularly in Africa. On one level, it will offer insight into the factors influencing the modality's learning outcomes and the relationship between learning outcomes and demographics. At the institutional level, the analysis provides findings on the efficacy of online learning, adding to the existing research on whether online learning is a viable strategy to enhance access and relevance.

CHAPTER 2 | Literature Review

Introduction

This chapter synthesizes the literature on major themes of the study on online learning as a mechanism for expanding educational access and intensifying human capital development to harness digital and demographic dividends in Africa *(see Appendix III)*. The chapter contextualizes the study's themes by reviewing the history and development of higher education in Africa. The literature on higher education in Africa emphasizes two main features: first, the continent's significance as the home of several of the earliest institutions of learning, and second, the transformation of advanced learning in Africa from one that served society to one that is disconnected from its setting. The notion of learning and education as a means for developing skills and capabilities (human capital), which benefits both the individual and society, was central to early learning and knowledge transmission in Africa. However, modern African higher education has shifted away from this original purpose. It has attained a distinctly Western gaze and orientation, rendering it foreign to its context in many ways.

The discussion of the current state of the African university is followed by a synthesis of the research on the demographic dividend and recent studies that offer evidence that reaping the benefits of a demographic dividend is directly linked to the quality of human capital investment. A discussion of the literature on the evolution of online learning serves as a bridge to studies on the effectiveness of online learning in other parts of the world, as well as studies pointing to potential challenges in the modality’s deployment in Africa. The literature review concludes with a discussion of connectivity in Africa and recent studies attempting to map the continent’s ICT infrastructure.

Extant Literature

Knowledge, learning and the university

The cornerstone of education is the generation and transmission of knowledge as a system of equipping individuals with information, skills, know-how, and capabilities to better themselves, society, and the human condition. Greco (2020) defines the generation of knowledge as "bringing [knowledge] into existence" and transmission as "distributing knowledge that already exists" (p. 1). Knowledge generation occurs through methods of knowing such as observation, insight, reflection, and reasoning and is transmitted via narratives, i.e., testimonials (Greco, 2020). Although there is debate about the adequacy of testimony to convey understanding and thus knowledge, Greco (2020) points to Aristotle's episteme and contends that understanding transmitted through "extended and systematic" methods found in formal and informal educational settings can indeed transmit knowledge (p. 130). Thus, knowledge generation and transmission do not always require an educational setting, suggesting that learning and understanding existed before the establishment of formal learning institutions.

The historiography of 'university' obscures the role of ancient centers of learning across Africa and Asia in the generation and transmission of knowledge. Makdisi (1970) asserts that the university was a product of medieval Europe, "there was nothing quite like it anywhere else" (Greco, 2020, p. 131). Peters (2019) argues that "the university as a form of organization was peculiar to medieval Europe," but other collective learning institutions in parts of the world predate the European form (p. 1063). This form of collective learning predates the common era in Africa and eventually gave way to centers of learning such as the University of Timbuktu, a collective of teaching mosques, and the University of Sankore, founded in 989, as well as the world's oldest universities, the University of Al Qarawiyyin in Fez, Morocco, founded in 859, and Al-Azhar University in Egypt, founded in 970 (Daniel et al., 2020; Ndofirepi et al., 2017).

Mosweunyane (2013) expands on this early form of African learning by situating knowledge transmission and training as central to African civilization and an essential part of the development of pre-colonial Africa. Even though the curriculum, setting, and trainers differed from what we see today, it was nevertheless organized systematically and transmitted knowledge from one generation to the next. The knowledge generated and transmitted was scientific, and it was shared throughout the community, including with newcomers, as "[t]he traditional schools were used to provide the necessary skills and knowledge that African societies needed for their survival" (Mosweunyane, 2013, p. 52). This type of learning is distinguished by its primary objective of addressing the needs of the community by investigating solutions to improve quality of life, such as environmental adaptation, living space construction, healing and medicinal arts, and public edifices such as the pyramids, thus linking learning to societal growth and development.

Higher education in Africa

The Colonial era

Despite this learning legacy, much of Africa's modern HEIs are rooted in the colonial period (Mampane, Ruth M. et al., 2018; Mosweunyane, 2013; Samoff & Carrol, 2003; Shizha & Makuvaza, 2017). Institutions established during the colonial era and its immediate aftermath now form African higher education. These institutions were essentially extensions of home-country universities created primarily to support the colonial project. The newly founded universities were staffed by Europeans, then later by nationals trained in Europe, with the objective of training locals as staff for state administration rather than equipping them with the knowledge and skills to address local community needs (Ndofirepi et al., 2017). The institutions and their curriculum were “aliens forms of centers of higher learning…removed from the realities and the needs” of the people and society (Shizha & Makuvaza, 2017, p. 203). The extent of dislocation of these institutions from local realities can be demonstrated by the fact both the curriculum and the degrees awarded were imported from the colonial home countries. For the most part, “these institutions had nothing to do with the socio-economic challenges of Africa…[and] remained instruments of colonization and domination” (Ndofirepi et al., 2017, p. 54). Additionally, the objectives of these institutions were maintaining colonial control and authority, which was at odds with the goals of locals attending them, who believed it would lead to equality. Therefore, whereas colonial education aimed to produce subordinate personnel who would preserve the status quo, local students aspired to attain exceptionalism to give them equal status to the colonizer.

Attending these institutions, either at home or abroad, had a profound social impact, with graduates becoming increasingly isolated from their communities and alienated from their culture. The newly educated elites relinquished old traditions and customs, forming a new social class. Later in the colonial era, Western education would become an exclusive asset, both as a personal means to jobs and privileges and as a national platform for independence and development. "It was also transformed into an “index of development as well as the tool for measuring national and human growth–a condition which forever transformed and destabilised the self-sustaining pre-colonial African society into one of dependency, since it did not have enough of this type of education” (Abrokwaa, 2017, p. 206). Hence, this period marks the start of the era of alienation between HEIs and the educated elite on the one hand and the societies in which they were located and should have served on the other.

The post-colonial era

At the dawn of the post-colonial era, African universities were regarded as the drivers of development and nation building (Daniel et al., 2020; Mosweunyane, 2013; Ndofirepi et al., 2017; Samoff & Carrol, 2003; Sawyerr, 2004; Shizha & Makuvaza, 2017). Leaders of the newly independent nations, and international policymakers, tasked HEIs with workforce development (human capital development) for economic growth, and given the importance of their mission, they received significant public funding to support this mission (Samoff & Carrol, 2003, p. 1). Sawyer (2004) points out on the eve of independence, the proportion of the national student population capable of financing a university education was practically nonexistent, so the small population of students eligible for admission required full support.

The policy of fully funded higher education may not have been fully considered because it stood in stark contrast to the local reality, and more importantly, it would eventually lead to prolonged scrutiny of the sector's value to development in relation to its share of public funding. Post-colonial education in Africa was characterized by an underdeveloped education system with limited reach that was still heavily influenced by missionary education (Asante, 1994; Higgs, 2009). The proportion of students who complete the entire education cycle was relatively low. Although higher education was more expensive to maintain and operate, full support for the few eligible students did not strain public expenditures. However, as access to education increased, so did the pool of qualified candidates and admissions, along with the share of funding for higher education as a proportion of educational expenditures increased, straining already limited public budgets.

Furthermore, while higher education was, in theory, a tool for human capital development, it could not shake off the colonial period's influence, thus continuing training for maintaining control and authority rather than addressing pressing local issues. Post-colonial HEIs continued the tradition of training administrators and state officials to replace Europeans in a variety of fields (Nampala et al., 2017). Therefore, higher education's role during the colonial period firmly shaped its outward orientation, which only expanded in the post-colonial era, effectively increasing the isolation of HEIs and the societies in which they lived.

Higher education's continued isolation from society and its increasing share of education budgets triggered a debate around its relevance and value to development. The perspective that the greatest return on investment in education was at the primary level started the shift in education priorities, ushering in decades of underfunding and underdevelopment of HEIs in Africa in the late twentieth century (Jowi et al., 2013; Psacharopoulos, 1994). Less than a decade after advocating for total public investment in higher education to support human capital development, the World Bank led the charge to divest from higher education in favor of primary education (Samoff & Carrol, 2003). As a senior economist at the World Bank, Psacharopoulos (1994) advanced a rate of return on education analysis that argued the rate of return in education varied by level, with the highest returns realized at the primary level and the lowest at the tertiary level.

The rate of return analysis became the standard formula in the World Bank's education policy in determining the "social rates of return to different types of education...to guide expenditure decisions" between different levels of education (Husain, 1993; Weale, 1993, p. 729). Psacharopoulos' rate of return model was reinforced by the neoliberal policies of the late twentieth century, such as Structural Adjustment Program (SAP)[7], following the *Washington*

[7] Structural Adjustment programs (SAPs) are economic policies implemented by the World Bank and the International Monetary Fund (IMF) in the early 1980s that are specifically aimed at developing countries. SAP is essentially a package of policies whose implementation are a precondition for World Bank and IMF loans, which may not be substantial but are a prerequisite to access other concessional loans. The conditionality consisted of

Consensus[8]. These policy prescriptions put significant pressure on governments to comply with World Bank and IMF conditions, which mandated primary and secondary as priority areas for education expenditures as part of the condition for development aid and loan qualification. The tremendous pressure applied to African governments to withdraw public support for higher education "intensified the tension between understanding education as a service whose costs can be met only after production and productivity have increased and the alternative notion that education contributes to production" (Samoff & Carrol, 2003, p. 55).

However, the rate of return model ignored findings from across Africa that show higher education provides a higher rate of return of up to 25-30% compared to primary education, which had a rate of return of 7-10% (Appleton, 2000; Barouni & Broecke, 2014; Diagne & Diene, 2011; Kingdon et al., 2010). A number of studies raised concerns about Psacharopoulos' methodology, such as the limited sampling of African countries, the availability of data needed for accurate estimates, the variables included and omitted in the model, and the aggregation for Africa (Bennell, 1996). Weale (1993) points out that the rate of return analysis is vulnerable to external effects such as health, as well as upward and downward bias, resulting in inaccurate public and private benefit projections. These influences are significant for developing countries, where healthcare provision and high fertility rates impact the rate of return model analysis. Despite this considerable flaw in the methodology and questions about its legitimacy, the World

currency devaluation that made exports cheaper and imports more expensive, easing of restriction to attract foreign investment operation of foreign businesses and banks, and cutting government spending through reduction of public sector employment and subsidies for education and health. SAP has not proven to be successful and has mainly resulted in unemployment, lower availability and quality of public services including education, and erosion of sovereignty of nations participating in the program (Mohan, 2009).

[8] John Willianson coined the term "Washington consensus" in 1989 to describe a set of neoliberal policies advanced by experts in international institutions primarily based in Washington, DC, such as the World Bank, IMF, and US Treasury. The policies aimed at liberalizing developing economies, reducing the role of the government, and facilitating foreign direct investment entry (Hurt, n.d.).

Bank's significant influence persuaded bilateral and multilateral donors to prioritize primary education at the expense of higher education. Ironically, at the same time, the World Bank was issuing technical papers warning about the deterioration of African universities, blaming cuts in public funding as the root cause of the decline in quality and enrollment capacity (Saint, 1992).

Conversely, the World Bank employed a different approach to Asia. The Asia rate of return report failed to establish a sufficient rationale for selecting one level of education over another. A World Bank report on the rate of return analysis for Asia reached the same conclusion as earlier critics of Psacharopoilos' approach. Mainly there was insufficient data to suggest primary education provides the highest rate of return to society and the economy. Furthermore, unlike the World Bank reports for Africa, which advocated heavily for primary education investment, the Asian reports declined to endorse the policy of focusing investment at the primary level based on the data findings:

> "The author of the Pakistan study concluded: "the differences in the social returns are too narrow to recommend resource allocations towards any particular education level" (Hamdani, 1977, p. 158). The Singapore study argued strongly: "secondary education is the most profitable from a societal point of view, followed by university education, followed by primary education" (Clark & Fong, 1970, p. 79). Similarly, "the most efficient and equitable growth strategy in Indonesia involves increased investment in junior secondary general education at the highest percentage rate" (McMahon & Boedieno, 1992, p. 149)" (Bennell, 1998, p. 117).

This divergence in approach and the reliance on fundamentally flawed data presents several concerns. For instance, the World Bank has relied on a severely faulty mechanism to analyze and coordinate African human capital investment strategies for over two decades. Despite multiple studies revealing severe flaws in the data source, methodology, and rate of return findings, the World Bank continued to use this model as the foundation for African education policy. This approach had disastrous consequences for African countries.

Table 1: Government expenditure and enrollment ratio

GHANA	**1977**	**1986**	**1996**	**2001**	**2005**	**2009**
Government expenditure on education as a % of GDP						
Primary education	19.57%	33.08%		41.54%	39.45%	33.13%
Secondary education	48.04%	41.10%		39.58%	32.52%	38.01%
Tertiary education	15.24%	2.09%		14.20%	22.08%	23.87%
Gross enrollment ratio is the ratio of total enrollment %						
Primary enrollment	68.20%	69.31%	77.89%	77.91%	86.55%	100.29%
Secondary enrollment	34.52%	35.69%	..	33.30%	40.03%	48.80%
Tertiary enrollment	..	..	..	..	5.87%	8.80%
ETHIOPIA						
Government expenditure on education as a % of GDP						
Primary education	34.70%	45.20%	51.19%	..	..	33.95%
Secondary education	36.54%	33.51%	26.28%	..	..	24.32%
Tertiary education	20.33%	16.27%	15.02%	..	..	39.12%
Gross enrollment ratio is the ratio of total enrollment %						
Primary enrollment	22.86%	36.99%	35.12%	60.58%	79.05%	93.43%
Secondary enrollment	..	13.01%	10.86%	16.44%	25.10%	33.60%
Tertiary enrollment	0.24%	0.81%	0.70%	1.47%	2.81%	5.3%

Data selected from UNESCO Data

While investments in lower cycles increased educational access, neglecting tertiary education led to deterioration in HEI. HEIs were largely ignored in the 1980s and 1990s as education investment shifted to lower levels of the education cycle, resulting in capacity reduction at the tertiary level. Simultaneously, increased access and quality at the primary and secondary levels resulted in more students completing the educational cycle, increasing the number of qualified applicants seeking admission to tertiary institutions. For example, UG student enrollment was 4,514 in 1996 and 24,480 in 2006, representing a 23% increase in annual enrollment (Mohamedbhai, 2014). Table 1 shows the increase in funding at the primary and secondary levels in Ghana and Ethiopia compared to the tertiary level and the rise in enrollment across education cycles, highlighting the dramatic increase in the 2000s.

While still a preferred formula, the Psacharopoulos rate of return model has given way to a broader discussion about the value and relevance of higher education. This shift has created a platform for higher education to emerge after fifty years of chronic underfunding, critical brain drain, and overall neglect. However, African HEIs are re-emerging in a digital era that has revolutionized knowledge generation and instruction. Globalization and technology have given rise to the knowledge economy, in which “explosive growth in the stock of global knowledge…has led to a steady shift from the importance of acquiring a particular body of knowledge to that of developing the skills for acquiring new knowledge and the capacity for using knowledge as a resource in addressing societal needs” (Sawyerr, 2004, p. 3). Consequently, the emphasis on education and training has evolved away from traditional career-focused training and toward providing students with diverse transferrable and transferable skills. This trend has implications for HEIs, which must reorient their mission and purpose to correspond with the digital era characterized by a knowledge-based economy.

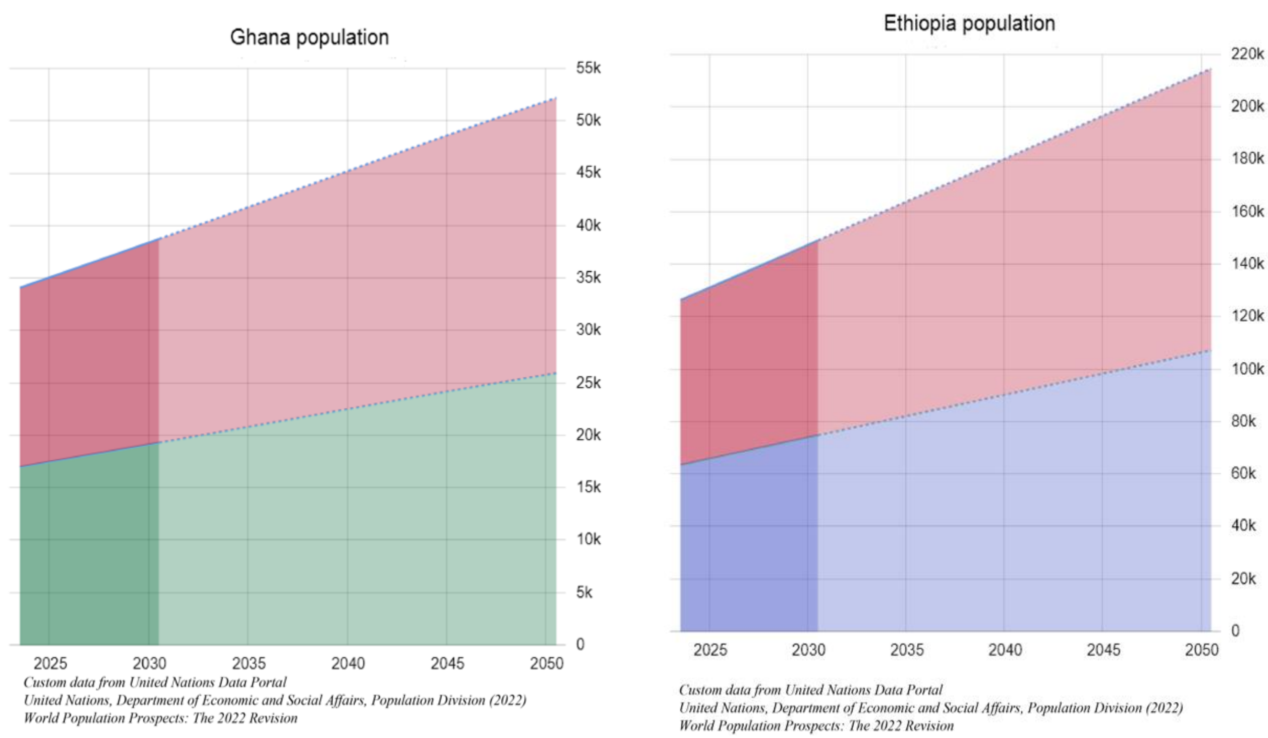
These global transformations in knowledge acquisition have far-reaching implications for African HEIs. Ramphele (2023) suggests probing the purpose of learning in this new digital world to enable “the acquisition and practice of new methodologies, new skills, new attitudes and new values necessary to live in a world of change.” This exercise of interrogating the purpose of education in the context of the early legacy of African institutions is an opportunity to reconceptualize “holistic teaching and learning…to bring out the best in each person” and to meet the needs of post-industrial societies (Ramphele, 2023). However, fundamental changes in instruction are required, including greater implementation of digital skills training with strategic approaches to delivering conceptual, analytical, digital, and socio-emotional skills to an increasing number of students and life-long learners.

Over the last fifty years, the neglect and underfunding of HEIs, combined with educational expansion at lower levels, has created a bottleneck at the tertiary level, just as the youth population is increasing. This bottleneck occurs in the context of a demographic transition in which youth comprise a larger proportion of the national population. Along with educational progress, significant progress in health services resulted in positive health outcomes such as lower infant mortality and increased childhood survival, resulting in the youth bulge, the first stage of the demographic transition. Transitioning this youth bulge into a demographic dividend requires education and skill development, but HEI capacity has not kept pace with the increase in the youth population. However, the incorporation of technology and online learning has the potential to bridge this gap by addressing some pressing issues in higher education, such as "a lack of human resources to teach, a lack of infrastructure to provide study places, and a lack of good quality learning materials"(Salgado & Rikers, 2017, p. 55). Therefore, online learning has the potential to serve as a mechanism for increasing access within infrastructure and personnel capacity constraints to increase admissions and leverage the demographic dividend (Shizha & Makuvaza, 2017).

Demographic dividend

The rise in qualified candidates seeking tertiary placement is an ongoing challenge for many African HEIs. As noted above, this increase in qualified applicants comes after decades of investment in human capital, which has reduced infant mortality, improved population health, and improved primary and secondary education, laying the groundwork for a demographic dividend (S. A. Ahmed et al., 2014). A demographic dividend is economic growth that results from a shift in population age structure when lower child mortality, lower fertility rates, and increased investment in human capital result in high individual productivity, which boosts national economic growth (S. A. Ahmed et al., 2014; Dews, 2019; Drummond et al., 2014). In 2019, 60% of Africa's population was under 25, growing to an estimated 1.2 billion in 2050 (Dews, 2019; United Nations, 2017). Figure 2 illustrates the increase in youth population in Ghana and Ethiopia from 2023 to 2050. This phenomenon is technically a demographic transition that "provides a window of opportunity…if properly tapped, can generate a demographic dividend" (Drummond et al., 2014, p. 4). Additional demographic data for Africa, Ghana, and Ethiopia can be found in Appendix III.

Figure 2: Ghana and Ethiopia 12-24 population projection to 2050



Some observers note the demographic dividend has already occurred with no impact on economic growth and is already in decline (Fox, 2019). However, numerous studies have systematically weighted factors, such as the vast diversity of the continent, the influence of education, and the impact of technological advances, to analyze the scale and extent of the demographic dividend and have concluded it has yet to take place (S. A. Ahmed et al., 2014). The conditions for a demographic dividend evolve over an extended period. The change in population structure takes place over decades, eventually leading to a larger labor force where individual productivity and income increase (Renteria et al., 2016). Even though progress in achieving essential milestones in infant and under-five mortality[9] across Africa initiated the demographic dividend, factors such as a continued decline in fertility rates and the uptick in education investment determine the demographic dividend's activation and duration. Yet, the direction and pace of these elements are not fully understood across the continent. Thus, forecasting the size and timing of the African demographic dividend would be difficult however, all signs indicate that it is on the horizon.

According to recent studies, the key to reaping the benefits of a demographic dividend is an individual's ability to engage effectively in economic activity, which requires human capital accumulation, such as education (S. A. Ahmed et al., 2014; Drummond et al., 2014; Renteria et al., 2016). A nation's economic productivity measure is its gross domestic product (GDP), "the sum of gross value added by all resident producers in the economy." GDP, divided by the population, yields GDP per capita, the productivity of its working-age population (The World Bank, 2020). Hence, GDP per capita growth leads to GDP growth. Therefore, continued

[9] In 2016, infant mortality was 56 deaths per thousand live births and under-five mortality was 83 deaths per thousand live births. In 2019, infant mortality was 47 deaths per thousand live births and under-five mortality was 90 deaths per thousand live births (UNICEF, 2020). These figures represent a 17.5% improvement in infant mortality rates and 17% improvement in under-five mortality rates.

investment in human capital is critical to improving per capita GDP and capturing the demographic dividend, with countries with greater levels of well-educated populations reaping the most significant benefits.

To illustrate this connection, Lutza et al. (2019) developed an economic growth model to assess the interaction between age structure and education in economic growth. The authors used a dataset on education attainment by age and gender from 100 countries from 1980 to 2005 and discovered when education and age were treated as unrelated variables in the regression model, the effect of population age structure on GDP per capita was significantly reduced. The study found that "the effects of a given change in age structure on economic growth depend on whether it takes place in a highly educated context or the framework of a largely illiterate society" (Lutza et al., 2019, p. 1280). The study establishes a link between education, personal income, and an individual's contribution to national development through increased GDP per capita. The study strongly suggests the benefit of the population dividend is accrued from the rise in the number of educated individuals participating in the economy (GDP per capita) and not increasing population.

Furthermore, Renteria et al. (2016) examine the effect of age structure on support ratio and the impact of education on production and consumption in two distinct societies, Mexico and Spain, beginning in 1970 and projecting to 2100. The study found the population's level of education had a positive effect on the demographic dividend during the first phase of the demographic dividend when the working-age population grew faster. Educational attainment of the population was also found to guard against the "adverse effects of aging, as education expansion delays the start of the negative growth of the support ratio" (Renteria et al., 2016, p.

668). Therefore, investing in education during the first stage of the demographic dividend not only increased GDP but also offset the economic decline associated with an aging population.

Hence, the critical factor in leveraging the demographic dividend is an investment in education for an overall increase in the educational attainment of the population (Lutza et al., 2019). This finding has implications for Africa, where a lack of capacity and infrastructure hampers HEIs' ability to participate in the demographic dividend. On the other hand, leveraging digital technology innovation provides a mechanism for overcoming physical constraints and delays in personnel development to meet the challenge of providing opportunities in education, training, and employment, including self-employment, for a growing pool of qualified applicants.

Demographic dividend and gender

Gender equity is central to realizing the demographic dividend. A study by Agence Française de Development points out, "[t]he issue of demographic dividend must be put into perspective according to gender relations, norms, values, and social practices, which govern the often unequal relationships between men and women from the point of view of households, families and communities" (Rabler, 2020, p. 3). To fully appreciate the demographic dividend's gendered dimensions, it is critical to consider how social and economic norms influence men's and women's experiences and create disparities in access to human capital development tools such as education and healthcare. Therefore, the conversation on managing and harnessing the demographic dividend for growth in Africa provides an opportunity to engage in gendered and inclusive human capital development.

According to the gender dividend concept, equitable human capital investment has the potential to close the workforce gender gap by moving women into better opportunities that increase earnings, enabling women to make lifestyle choices while also expanding the economy's productivity (Belohlav, 2016). Women constitute a sizable proportion of the working-age population however, due to disparities in educational attainment between men and women, women are limited to unpaid and irregular jobs, resulting in wage disparities and poor and marginalized employment prospects (Santos Silva & Klasen, 2021). Therefore, women are underrepresented in education and are more likely than men to engage in unpaid work such as dependent care, domestic work, and subsistence farming, as well as have less access to formal employment.

Women's participation in human capital development activities is limited by several intersecting factors, including cultural and traditional norms that influence family and individual decisions on education investment. Through a demographic behavior model analysis, Grimm (2003) employs the utility maximization concept to demonstrate how human capital investment decisions at the household level directly impact economic growth. He points out families are central to economic growth as they "are…producers of human capital, which constitutes, according to modern growth theory, one of the crucial production factors" (Grimm, 2003, p. 164). Household decisions about education investments are influenced by a complex interplay of demographic factors, external pressures, and rates of return, which frequently have a gender component. Langerlof (2003) uses a social norm model to demonstrate generational inequality in women's human capital investment, where parents expected their daughters to marry men with higher incomes, resulting in less investment in their daughters' human capital, i.e., education.

Limited access to education is a significant barrier to women's economic participation in Africa and reduces productivity and national economic growth. Girls are often less likely to attend school than boys, and those who do may not receive the same quality of education.

According to UNESCO (2023a), 9 million girls and 6 million boys will never attend school across Africa between the ages of 6 and 11. This exclusion rate for girls continues at the primary level, with 23% of girls, compared to 19% of boys, out of primary school, and in adolescents, the rate for girls is 36% compared to 32% for boys (UNESCO, 2023b). Women's access to educational opportunities is hampered by the interaction of social and cultural norms, limiting their participation in human capital development activities.

As discussed above, the level of educational attainment of the population, rather than the population age structure, is a key determinant in not only realizing demographic dividend but also in determining the magnitude of its impact (Lutza et al., 2019; Renteria et al., 2016). Gender inclusivity in education is critical for realizing the demographic dividend, as women make up approximately half of the total population and will continue to do so in the foreseeable future *(See Appendix III).* The youth population in Africa is expected to reach 321 million by 2030, with young men accounting for 50.5% and young women accounting for 49.5%. By 2050, with a youth population of 456 million, women will still account for nearly half of the youth population. Equal access to human capital accelerators such as education is required to remove barriers that limit women's economic participation. According to Belohlav (2016), “increased economic growth...with investments in women and girls” could be realized by easing social burdens and investing in women’s human capital, such as education. Closing the gender gap in education is critical for equitable human capital development since education elevates and determines the extent of a demographic dividend.

Online learning

Online learning is a strategic tool for increasing educational access in the context of limited facilities, infrastructure, and staff to meet the growing number of youth and young adults seeking education and training. Online learning is a form of Educational technology (EdTech) at the intersection of technology and education, where technological innovations and advances are integrated to support, supplement, customize, personalize, and diversify instruction (EdTech20, 2017). With each stage of innovation in EdTech, the goal has been to create a learning environment that diminishes the distance between instructor and student as well as the student and the material. Digital innovations have expanded EdTech from simple computers to integrate interactive displays and simulations that increase interaction between instructor and learner (EdTech20, 2017). Although technological advancements enable instructors and students to visualize and connect with materials directly, they also have implications for the system's required bandwidth and connectivity for optimal operation and user accessibility.

Innovations in technology, such as the internet and personal computing, gave rise to online learning, which employs computers and the internet to deliver courses and instruction (Moore, 2019). Extant literature indicates certain preconditions must be met to effectively harness these new technologies, such as quality early learning, digital literacy, and technical capacity, which have been found to strongly determine individual success in online learning programs (Kauffman, 2015; Nguyen, 2015). Moreover, due to the solitary structure of the modality, students must be motivated to take the initiative and responsibility for their learning and be digitally knowledgeable to navigate the learning platform. The significance of student characteristics as a determining factor in success in online learning is a common theme across studies, raising the question of whether the student or the modality is the more decisive factor in successful learning outcomes (Alghazo, 2005; Kauffman, 2015; Nguyen, 2015). While learners' motivation and self-directedness appear to be the primary determinants of learning outcomes in online learning, components of online learning, such as on-demand and self-paced learning, tend to contribute to enhanced learning and engagement. Moreover, technical aspects of online instruction, such as the ability to pause, rewind, and review lectures at any time and the flexibility and convenience of attending an online class, appear to contribute to increased learning and engagement (Moore, 2019).

Convenience and learning characteristics influence students' selection of online courses. The flexibility online learning offers is among the primary reasons attributed to the growth of online learning. A study on flexibility found the ability of students to “structure their learning processes whenever, wherever, and for as long as they want” was an essential consideration for students (Turan et al., 2022, p. 14). Moreover, flexibility must be accompanied by self-directness and self-regulation, defined as allowing for setting and achieving learning goals and overcoming perceived challenges to yield learning outcomes (Ally, 2004; Bernard et al., 2004). Finally, while online learning may deliver learning objectives for students with a combination of learning characteristics, there are concerns about its suitability for students who may not succeed in an online learning environment.

Online learning opponents criticize its suitability for certain courses and its appropriateness, particularly during the first two years of college. This point of view is based on the function of classroom education in socializing pupils as well as the intangible benefits of face-to-face encounters with classmates, professors, and materials that question students' beliefs and opinions. In face-to-face instruction, students are “taught by expert educators about how to access, analyze, criticize, synthesize, and communicate knowledge from multiple perspectives and disciplines” (Samuels, 2013).

Moreover, there is considerable faculty opposition to online learning, which is sometimes expressed passively through opting out and disengagement. Ruth (2018) compares the exponential rise of online learning to the professoriate's relative absence in developing and mounting courses as evidence of faculty disengagement with the modality. One of the reasons for this apathy is unlike face-to-face instruction, which has clearly defined input and output requirements and assessment metrics, labor toward online learning courses lacks guidelines and standards (Ruth, 2018). For instance, the non-teaching labor required to create online learning content does not neatly fit the job performance evaluation criteria, and most faculty are unfamiliar with converting their face-to-face courses to online. Moreover, administrators perceive online learning as cost-effective, and the modality's adoption in HEIs tended to embrace a basic economic calculation without considering the human dimensions of teaching and learning (Baxter et al., 2018). The economic justification for online learning has proven particularly powerful in the context of academic capitalism and declining in-person attendance.

Faculty opposition is also based on technology supplanting the "human element of teaching" (Baxter et al., 2018, p. 18). The criticism stems partly from the modality's failed introduction in higher education. The sporadic nature of online learning deployment overlooked institutional shared governance structures and the value of early faculty engagement. Lack of faculty buy-in and an absence of institutional direction and leadership has created a communication, policy, and incentive vacuum, leaving faculty members to fill the knowledge void independently.

Online learning and culture diversity

Embedded culture in online systems is frequently overlooked in the deployment of online learning. Although little emphasis has been paid to how students from varied backgrounds engage in online learning, a few studies from the United States show mixed results in terms of learning outcomes. Xu & Jagger conducted a study of 40,000 students enrolled in 500,000 courses in community and technical colleges and found that all students indicated some decline in performance, and learning gaps from the classroom were reflected online, where "Black students had more than twice the negative coefficient of Asian students…" (Xu & Jaggars, 2014, p. 644). However, the study lacked depth in understanding the basic profile of students outside of siloed disaggregation by race, gender, and age. It fails to consider the different components of online learning that might have impacted the learning outcomes under consideration.

Palacios et al. (2016) compared the learning outcome of Black, Latino, White, and Asian men across three learning modalities, face-to-face, asynchronous, online with multi-media, and synchronous online without multi-media. The study found that the most effective instructional modality for all ethnic groups was in-person instruction. However, African American men were the only group for whom asynchronous online with multi-media was identified as the second most effective modality for success, defined as earning a certificate, degree or transferring (Palacios & Wood, 2016). However, the study could not account for the difference in performance, and given the data set, it would be speculative to attribute any single factor to this trend.

Conversely, a meta-analysis of 51 studies found effect of +.24 for online and that the mean difference was over 51 and significance at p.01 in the learning outcome of those in online versus those in classroom instructions concluding that the methodology and analysis, instead of modality, accounted for previous findings (Means, Toyama, Murphy, Bakia, & Jones, 2009). The study further found that blended online instruction "effect size is larger than that for studies comparing purely online and purely face-to-face conditions" due in part to student's ability to self-pace learning (Means, Toyama, Murphy, Bakia, & Jones, 2009, p. xv).

Online learning brings many issues in terms of diversity and cultural relevance that exist in traditional classroom instruction (Goodfellow & Hewling, 2005, Wang, 2007). Apart from highly developed online programs, many online courses are mainly digital versions of classroom curricula, often with the same instructors delivering the course. Yeboah (2016) found that among the factors that supported positive learning outcomes for non-white students, many were focused on the environment, including cultural relevance, language, and a curriculum and setting that encompasses diversity. However, the physical separation and ability to control interaction and pace of learning appear to provide a conducive environment for motivated students with self-regulatory skills to achieve their academic goals. Although studies have examined various facets of online learning from the perspective of institutions, academic performance, and learner characteristics, there is a lack of understanding of the push and pull factors that lead students from diverse cultures to engage in online learning.

In many parts of the world, online learning is controversial and regarded as inferior to in-person instruction. This view extends to lecturers, students, and employers, where those with online training may face hiring discrimination. Some view it as an "inferior form of education providing an isolated learning experience [and]…a harbinger of global, Western-dominated educational homogenization" (Trines, 2018). There is also a perception that best practices in online learning from the US and the West frequently "embed deep political, epistemological, and cultural assumptions that may be incongruent with the cultural knowledge of users in many communities in Africa," potentially excluding locally produced materials that reflect community needs and address local issues (Mawere & Stam, 2019, p. 421).

According to Chukwuere et al.(Chukwuere et al., 2018), even though online learning systems are culturally embedded, the process of system deployment fails to recognize the impact of culture on system adoption, and they propose a "culture-oriented e-learning system" to bridge the cultural divide (p. 146). Joy & Kolb (2009) conducted statistical analysis to highlight the impact of culture on individual learning styles and discovered culture had a marginal effect on learning styles while social and cultural features such as collectivism, social norms, and assertiveness influenced individual learning styles. Taking the "cultural learning needs" of users into account in operational systems entails investigating how culture is embedded in software, hardware, instructional design, learning communities, and communication platforms (Blanchard et al., 2005; Chukwuere et al., 2018, p. 149; Sun et al., 2008). Therefore, evidence suggests the default orientation of online learning systems and methods, such as language, culture, and assessment, influences adaptation and learner experience in non-English speaking and non-Western environments.

Online and face-to-face instruction

Studies conducted outside Africa have found mixed results when comparing online learning and classroom-based instruction across several factors. As previously stated, success in online learning requires a student's participation in the learning process and a level of determination and self-direction to perform within the modality's isolated and independent environment. This finding suggests attributes associated with independence are crucial for achieving learning objectives in online learning, whereas face-to-face instruction is predicated on team and group learning. Therefore, the characteristics of learners for online instruction are somewhat different from those that determine success in classroom instruction. While immediate reaction, active participation, and active engagement, as perceived by the instructor, are critical to classroom performance, online learning allows students to determine the pace and time frame of their engagement with the material. Also, online learning requires significant self-regulation, defined as "students' proactive use of specific processes such as setting goals, selecting and deploying strategies, and self-monitoring one's effectiveness, to improve their academic achievement"

(Zimmerman, 2008, p. 167). Online courses have limited instructor oversight in terms of attendance, timeliness in reviewing lectures and completing assignments requiring students to take greater responsibility for their learning. Identifying the context and environment in which online learning would be most beneficial contributes to a better understanding of its suitability, application, and limitations.

One of the most impactful studies comparing online learning and face-to-face instruction was based on a bibliography of studies conducted from 1928 to 1998 by Russell (2001) which concluded there was no significant difference in final grade between classroom instruction and online learning when the independent variable was modality. The study examined 355 studies and concluded instead of the modality, course design, instructor, and student were factors in student learning outcomes (Russell et al., 2001). Since then, numerous studies have been conducted to confirm and disprove the findings of 'no significant difference' between online and face-to-face instruction. Studies by Larson and Sung (2009) examining student performance in online versus face-to-face instruction confirmed the absence of significant differences in learning outcomes in modality, even as there were differences in student evaluation of the courses. Moreover, a meta-analysis of the literature on online and face-to-face programs examined 30 studies between 1985-2004 across various disciplines and found very little difference in the outcome (Yu & Deng, 2022). A seven-year comparison of students in a science course found no significant difference between modalities, with the same holding true for gender and class rank (Alghazo, 2005).

Conversely, Fendler et al. (2018) used an empirical model to forecast grades of over 500 students, where online students' grades were predicted for face-to-face and vice versa and found as high as 42% of students, whom he calls "jumpers" experienced at least one full grade negative or positive change. Although this study discovered a significant difference between modalities, given the uniqueness and complexity of online learning courses, it is difficult to determine the impact of the course delivery system and the quality of instructional material on students' learning outcomes. Similarly, a study comparing the performance of fourth-year medical students using the virtual tutorial platform and those attending in-person tutorials found those using the online platform performed lower in several areas, including communication, participation, preparedness, and critical and group skills (Foo et al., 2021). However, when asynchronous programs were compared to face-to-face programs, there was a significant positive effect (Bernard et al., 2004). Conversely, a study of an accounting course in dual mode found significantly higher performance in students in the face-to-face mode than in the asynchronous mode but also found that women outperformed men by 30% in the online course and 15% in face-to-face (Faidley, 2018).

A comparison of science courses offered in dual mode found GPA and previous online learning experience were significant predictors of students' performance in the online modality, which had a 93% completion rate compared to 85% for those in face-to-face instruction. Furthermore, a comparison of online and face-to-face education courses revealed students' time management and organizational skills, and those with higher level reading skills performed better in online learning (Stern, 2004). Researchers have also examined engagement with materials and test scores. They have found an "improved perception of learning and the online format, stronger sense of community among students, and reduction in withdrawal or failure" (Nguyen, 2015, p. 310).

The discrepancy in findings across online learning modes discussed above appears to be due primarily to the lack of a uniform definition of online learning, the potential incompatibility of online instruction in specific disciplines, and a lack of a comparison framework (Alghazo, 2005; Faidley, 2018). The term is broad and unwieldy because online learning encompasses a wide range of technology-mediated learning, from synchronous to asynchronous to web-based. Furthermore, the structure of contact hours/unit and assessments is ambiguous. Even though COVID-19 has expedited the implementation of online learning, the modality's features and characteristics are still being established and structured. As online learning moves from the periphery, norms, and standards are established, a coherent definition for the modality will arise, as will a clearer understanding of its effectiveness. Additionally, the difference in these studies illustrates the difficulty in quantifying elements of online learning and learner characteristics in analytical models. Moreover, it also points to a need to examine methodology and analysis to compare modalities that can move beyond learning outcomes.

Online learning technology

Most online platforms are based on systems designed for high-connectivity environments, which may be incompatible with the local infrastructure and digital capacity of users and institutions in less technologically developed areas. Technical difficulties frequently obscure and cloud perceptions of online learning, where technical challenges are perceived as a deficiency in the modality or the platform. For instance, the widespread use of online learning during the Covid-19 closures appears to have reinforced the negative perception of online learning. According to Ouma (2021), there has been an increase in the negative perception of online learning in Asia and Africa due to issues with connectivity, quality of instruction, and overall personal preference. Among the challenges cited by students include using “mobile phones to access course material…high cost of data bundles, unreliable network…lack of prior experience with online learning…poor communication between learners and educators" (Ouma, 2021, p. 798).

It should be noted that these opinions were formed by user experience with the national ICT system, which is further complicated by institutional readiness and agility in identifying alternative solutions, all of which significantly impact learning in the modality. Though several factors influence the effectiveness and functionality of online learning, ranging from learner disposition to connectivity, elements of the modality have the potential to expand access, albeit with significant customization and modification for the local context. These underlying issues have implications for the design and implementation of technology integration and online instruction in African institutions.

Online learning and gender

Several studies have suggested that online learning has the potential to close the education gender gap, particularly in developing countries. Online learning eliminates the time and distance restrictions by bringing the classroom to the learner and allowing them to learn at their pace as well as by "improving gender inclusion in science, technology, engineering, and mathematics (STEM) fields and connecting women to rising skills and job opportunities" (World Economic Forum, 2022). Online learning appears to have increased educational opportunities for all learners, particularly women who were previously unable to participate due to family and other responsibilities. Gender differences in online learning experiences and outcomes may be influenced by various factors, including cultural norms and expectations, as well as persistence and completion.

Female students are frequently subjected to sociocultural influences, such as social pressures prioritizing male schooling, marriage, and childrearing, which disrupt their educational progress at all levels. According to International Finance Corporation (2022), family obligations and mobility are factors in all students' decisions to select online earning, with women reporting these top motivators at twice the rate of men. Women with inflexible obligations such as childrearing and caregiving appear to benefit from online learning, with "45% of women and 60% of women caregivers saying...[they[would postpone studies or not study at all if [not for] online" (IFC, 2022, p. 29).

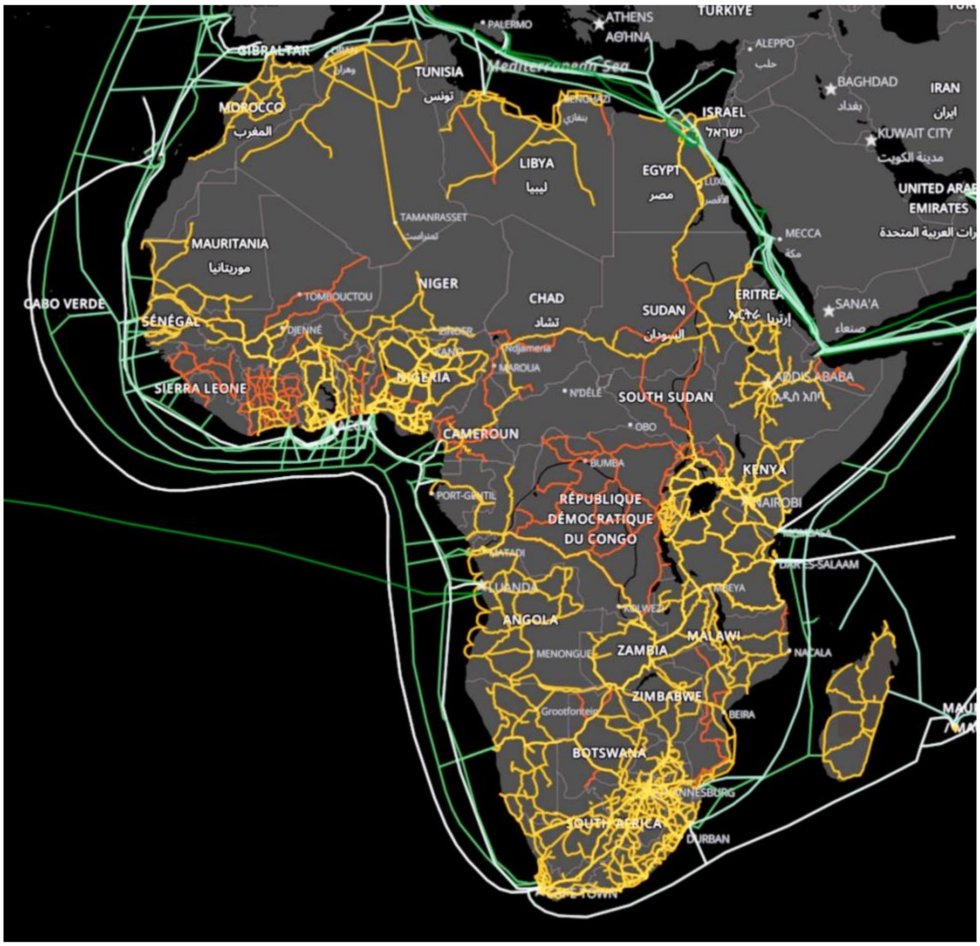
Furthermore, men and women enroll in online learning with different learning objectives. While women tend to prioritize community and social learning, men are focused on career advancement and degree attainment. A meta-analysis and systematic review of gender differences in online learning around the world discovered that there was no gender difference in self-efficacy, motivation, and learning outcomes between male and female students (Yu & Deng, 2022). However, the study discovered that female students had more positive attitudes and evaluated online learning higher than male students. This supports previous research that found female students are more likely to engage in online discussion and communication, whereas male students use the online learning platform to seek information rather than communicate (González-Gómez et al., 2012; Johnson, 2011). Likewise, Rovai and Baker (2012) conducted a multivariate statistical study to determine whether there were any differences in social and learning communities between male and female students. According to the study, female students reported a stronger sense of community in online courses than male students. Female students also "participated in the courses at higher rates than male students and identified their experience as socially richer (as evidenced from the sense of community) and educationally more effective (as evidenced by perceived learning) than men" (Rovai & Baker, 2012, p. 40).

Despite the mobility and flexibility of online learning, social and family obligations continue to impact women's education, frequently interfering with and ultimately preventing completion. According to Coursera's platform data, only 57% of women enrolled in fee-based professional certification courses completed their program, with 82% reporting lack of time as a factor and listing family obligations as the reason (IFC, 2022). However, Coursera's findings may not be generalizable to other programs, and women's online learning completion rates may be related to discipline, learning platform, and course delivery method. For instance, a global study of Massive Open Online Courses (MOOCs) focused on STEM (science, technology, engineering, and mathematics) found that women were less likely to enroll in STEM MOOCs; however, the small number of women who do enroll are almost as likely as their male counterparts to complete the course, with a slight decline in completion rates for less developed economies (Jiang et al., 2018).

Low connectivity

Africa's connectivity has improved dramatically, with submarine cable deployment, which began in 2009, proving to be a game changer for the continent. According to TeleGeography, a total of $12 billion worth of undersea cable has been deployed in Africa since 2016, with an additional $10 billion expected to enter service between 2022 and 2024. In 2022, 71 cable systems were active or under construction connecting Africa to the rest of the world with digital hubs in Egypt, Kenya, South Africa, and Nigeria (*Africa Telecom Map 2022*, 2022). Of the 38 countries in Africa with a coastline, 37 have at least one submarine cable landing site, except Eritrea. To truly appreciate the speed with which Africa has joined the digital revolution, consider the first submarine cables connecting Europe and North America deployed in 1956 and the first fiber-optic submarine cable in 1988. In contrast, full connectivity for Africa was only in 2009, less than 15 years ago (Submarine Networks, n.d.).

Figure 3: Submarine and terrestrial map of Africa



Source: African Undersea and Terrestrial Fibre Optic Cables", Network Startup Resource Center (NSRC), https://afterfibre.nsrc.org/ [accessed on: 05/30/2023.

Terrestrial lines are the second component of Africa's connectivity and have been a major hurdle in increasing connectivity. Once a submarine cable reaches a landing site, the connection is carried through terrestrial lines to other parts of the nation and landlocked countries. For 1.2 billion inhabitants achieving universal connection in Africa will require 250,000 new 4G base stations and approximately 250,000km of terrestrial fiber cable (UNESCO, 2019). The importance of fiber cable over satellite or microwave cannot be overstated in terms of Africa's connectivity growth. According to the World Bank, much of Africa's internet connection occurs via mobile links connected to cell towers that may not be served by fiber, reducing the signal from 3G/4G to 2.5G (Fukui et al., 2019). As a result, even though broadband connectivity is widely available, a lack of terrestrial fiber cable restricts speed, limiting productivity. Moreover, the terrestrial distribution is insufficient for Africa's population distribution, where "approximately 45% of Africa's population is further than 10km from fiber network infrastructure, which is a higher percentage than on any other continent" (Fukui et al., 2019). While progress has been made in connecting Africa to the rest of the world, the challenge of Africa's connectivity lies in distributing connectivity to the population via terrestrial lines.

The Global Connectivity Index (GCI) assesses the expansion of ICT infrastructure worldwide. It lists the top 79 countries according to their level of technology infrastructure development. The GCI categorizes as *Frontrunners*, countries that score 65-85% and are leading the way in ICT and AI innovation, *Adopters*, those in the range of 40-64% indicating quick expansion of digitization into industry and economy, and *Starter* with scores 23-39% are in the early stage of ICT development and focused on expanding connectivity to greater populations (Huawei, 2020). The primary measures for the index are Internet bandwidth and broadband download speed, which are "Foundation" indicators on which all ICT innovation takes place. The 2019 GCI did not list an African nation in the *Frontrunner* category and only South Africa, with a score of 43%, made it to the *Adopters* list, however, the *Starter* category included Egypt (37%), Morocco (36%), Algeria (31%), Botswana (30%), Ghana (29%), Kenya (29%), Namibia (28%), Nigeria (27%), Tanzania (24%), Uganda (24%), and Ethiopia (23%). The placement of eleven African countries across 24 available slots is a strong indicator of the emergence of digital technology in Africa. However, the low scores reflect the low penetration rate with uneven distribution, where connectivity outside metropolitan areas remains a significant challenge (Huawei, 2020). This finding is collaborated by a Pew Research Center (2018b) study that globally, there was a correlation between national GDP per capita and the proportion of the population online. The report includes a demographic profile of internet users in Africa who tended to be young, educated, well-off, and in urban centers, who go online for social and entertainment purposes (Pew Research Center, 2018b).

Low connectivity environments are characterized by inadequate availability of bandwidth, defined by the internet connection capacity, as calculated by the data transfer rate in uploading and downloading, and uneven distribution and connectivity outside metropolitan areas (Gakio, 2006; Huawei, 2020). However, an inclusive and individual-level measure of low connectivity includes "insufficient bandwidth, inadequate telecommunication infrastructure, irregular power supply, high cost of technology" (Suhail, 2008, p. 377). These factors significantly impact an individual's ability to participate effectively in online learning.

As previously discussed, while Africa has made significant strides in connectivity through the expansion of submarine lines, the challenge many countries encounter in increasing connectivity is the lack of terrestrial infrastructure to convey connections from landing sites *(see Figure 3).* Although connectivity is high in major cities such as Accra, which has one of the fastest internet connections in Africa, it drops off further inland and in rural areas, as illustrated by connectivity in Ethiopia *(see Appendix IV).* In terms of connectivity importance, reliable electricity is a close second. Frequent power outages, national or local, impact internet availability and the ability to access and download materials. The failure of various technology-centered learning initiatives was attributed to a lack of reliable electricity, which ranged from outdated wiring to limited outlets to extended blackouts (BBC, 2016; Corn et al., 2010; Trucano, 2015).

Aside from infrastructure, high data costs are critical in defining low connectivity since it directly determines individual digital readiness. A recent Krone (2020) study found only 17% of respondents across 34 African countries are prepared to engage in internet-facilitated remote learning. Regression analyses of digital literacy found that 55% were completely unprepared, while 28% would require additional resources to participate in online learning (Kronke, 2020). The study also found a significant urban-rural divide in household device ownership (64% vs. 29%) and digital literacy (48% vs. 18%); and a positive correlation between reliable electricity and digital literacy. An additional challenge is the cost of Internet connections. Internet users in Africa pay the highest rate in the world as a proportion of personal income. The average price of 1GB of data is 7.1% of the average income (Affordability Internet, 2019). These findings illustrate a significant challenge in adopting technology in low connectivity environments like Ghana and Ethiopia.

While connectivity, electricity, and digital skills are all significant challenges for nations seeking to harness the digital dividend, the structure of technology may be the most daunting to overcome. The fact that technology is designed and built "by and for the wealthiest 30 % of the planet," a relatively small and isolated group, is a significant barrier to leveraging it (Cutrell, 2011). This small collective's relatively narrow worldview is mirrored in the digital world, where biases, cognitive models, and information-management processes reflect their worldview and experiences, many of whom are unaware of larger global digital/cultural/operational constraints. For example, newer systems are designed to operate on 5G[10] for speed and

[10] 5G technology is "fifth generation of wireless cellular technology, offering higher upload and download speeds, more consistent connections, and improved capacity…and has the potential to transform the way we use the

efficiency, while most of the world is still on 2G or 3G. Similarly, most platforms, including LMS, perform best on high-end smartphones, tablets, and computers, even though these devices are out of reach for the vast majority of the world's population. However, this does not preclude the creation of effective systems, conscious of constraints, from being possible and practical. While ApplePay[11] requires a credit card, an Apple account, and a smartphone, mobile money systems such as Mpesa[12] do not have these additional requirements and work on any phone via a GSM network. Therefore, creating equitable, accessible technology is possible but requires inclusive programmers with broader perspectives and worldviews.

Technology and the gender digital divide

The spread of digital technology, while it has transformed society, it has also created a significant digital divide. The Internet Society defines the digital divide as "the gap between those who have and do not have access to computers and the Internet" (Muller & de Vasconcelos Aguiar, 2022). There are, however, various approaches to measuring this divide which reveals that "[t]here is no one digital divide...there are multiple divides" (Muller & de Vasconcelos Aguiar, 2022). One such divide is the gender digital divide, which has created a "gap between men's and women's ability to access and use the internet and digital technologies, as well as contribute to and benefit from their development" (WinDt, 2022). There are several barriers to

---

internet…[f[or example, technologies like self-driving cars, advanced gaming applications, and live streaming media that require very reliable, high-speed data connections are set to benefit greatly from 5G connectivity" (AWS, 2023).

11 Apply pay is an electronic payment system that requires a credit card and Apple account and is uses iPhone, iPad, Apple Watch, and Mac. It essentially functions as a credit card and uses Near Field Communication (NFC) a standard contactless technology that only works across short distances such as the phone and pay terminal. In terms of availability in Africa its only available in South Africa (Apple, 2023).

[12] M-Pesa is a mobile money system built on GSM network that converts cash to e-money offering services including deposits through retail agents, transfers to individuals and for purchases and bill payment, and withdrawals. It was initially designed as a microfinance-loan repayment system. Today M-Pesa is used to disburse salaries and includes a loan and saving service available in Kenya, Tanzania, Afghanistan, India, Lesotho, Ghana, Egypt, South Africa, Mozambique, and Democratic Republic of Congo (Nana Mbinkeu, 2013; The Economist, 2015)

gender digital inclusivity, such as access to devices, data, and the internet, affordability due to low income, digital literacy, which is increasing exponentially with technological sophistication, and security as a result of experience with cyberstalking and cyberbullying (Tyers-Chowdhury & Binder, 2021).

The gender digital divide is multi-dimensional; on one level, the technology has "characteristics and properties that go directly to the roots of women's inequality," and on another, its functionality and accessibility (Huyer & Hafkin, 2018, p. 3). As technology advances and becomes more prevalent in all aspects of social, community, and economic life, the gender digital divide widens, further excluding women from human capital development tools such as health and education.

Although the gender digital divide is global, "women within developing countries are in the deepest part of the divide further removed from the information age than the men whose poverty they share" (Olatokun, 2008). This places women at a great disadvantage since technology is required for access to education, health care, and financial services, and digital skills are also necessary for employment in a rapidly automated workplace. By 2030, 230 million jobs will require digital skills in Africa (IFC/The World Bank, 2019). However, Africa has the largest gender gap in mobile internet access, with over 190 million women not using mobile internet services, representing a 37% gender gap (Kwakwa, 2023). Furthermore, 86% of women in the West had access to the internet in 2020, compared to only 19% of women in many parts of Africa (CIPSEA, 2022). This gender digital divide aggravates educational inequality by introducing a new dimension to the challenges girls and women face in accessing education. It has implications for attempts to increase educational access with technology, where female students will face new barriers to education and training. Furthermore, women are disproportionately underrepresented in the ICT sector, with men four times more likely than women to be ICT professionals (OECD, 2018). Closing the gender digital divide is critical if technology's benefits are to be distributed evenly throughout society.

A mistaken perception of technology as neutral and benign is one plausible cause for the persistence of the digital gender divide. However, structural inequalities and discriminations in the physical world are replicated in the digital world. While much has been said about understanding and addressing women's lack of access to technology, ignoring the "patriarchal narrative of technology will...[continue] to disenfranchise women and at best relegate women to the role of fleeting consumers of the technologies" (Alozie & Akpan-Obong, 2017, p. 142). Recent research has revealed a tangled network of gender, race, and class biases that are an integral part of technological design that amplify existing inequalities as these disparities exist in society and are incorporated, consciously and unconsciously, in technology (Benjamin, 2020; Bolukbasi et al., 2016; Buolamwini & Gebru, 2018; Eubanks, 2018; Noble, 2018). The studies demonstrate how bias is embedded in digital systems, forming a "larger matrix of systemic" inequality as "[d]atabase design…is "an exercise in worldbuilding," a normative process in which programmers are in a position to project their world views a process that all too often reproduces the technology of race" (Benjamin, 2020, p. 77). Increasing racial and gender diversity in the tech ecosystem can help to address this default discrimination. Therefore, for ICT to promote gender equality, it must go beyond meeting functional and access needs and address the social and cultural norms and stereotypes perpetuating women's unequal status in technology and society.

Summary

The chapter presented a literature review of several themes related to the study, including higher education in Africa, online learning, demographic dividend, and human capital. African higher education is centered in the discussion, given its role in the study and the deployment of online learning. Modern higher education in Africa is a product of the political and economic environment in which it was established. The colonial mission and influence of its founding loomed large, reshaping social structures and paving the way for post-colonial external intervention. The World Bank's substantial influence in shaping African education policy in the second half of the twentieth century resulted in a shift of resources away from HEIs, ushering in a 50-year declining trend in many institutions. The ongoing effort to decolonize African HEIs recognizes the contradiction of current institutions in their existing iteration with the society in which they exist. Under these circumstances, African higher education is expected to lead in harnessing digital and demographic dividends.

Numerous research and reports identify education as the key driver of human capital development and essential for harnessing the demographic dividend. The ability to benefit from expanding the youth population depends on raising the population's education level, which leads to greater personal productivity, boosting national economic growth. Online learning has the potential to raise the educational level of an ever-increasing youth population, thereby realizing the demographic dividend.

The literature identifies several challenges to expanding online learning, including HEIs capacity gaps, low connectivity, and an unsettled landscape of online learning deployment. The chapter provides a nuanced discussion of the current connectivity level in Africa and its relevance to online learning. Connectivity is a complicated and layered process dependent on a number of factors, making online learning easily accessible in some settings and challenging in others. However, the return on investment in increasing the quality of education, such as improved quality of life and opportunities for the individual and technological innovation to drive economic growth, are clear and offer an occasion to re-imagine human capital development and educational delivery. The chapter included a gendered context of selected themes to illustrate the disparities in women's experiences and highlight areas of inequality and potential pathways to equal access and opportunity.

CHAPTER 3 | Conceptual Framework

Introduction

This chapter analyzes the key tenets of human capital theory to construct a conceptual framework for the twenty-first century. It is, to a large extent, a return to the fundamental concepts of human capital theory, which advances education as a benefit to the individual and society, a driver of economic competitiveness, and a critical component of individual freedom.

The overarching theoretical framework for the study is a reconceptualization of human capital for the twenty-first century defined by the digital and demographic dividend in the context of the rapid acceleration of globalization. The framework begins with Adam Smith's *Moral Sentiments* (1863), highlighting education's social and individual value, and *Wealth of Nations* (1776), the competitive advantage of a nation with an educated labor force. It follows the development of the theory through the twentieth century with Becker (Becker, 1993) and Schultz (1961) and concludes with Sen's (1999) expansive definition at the dawn of the twenty-first century.

The principal features of the twenty-first century are the ever-increasing pace of technological innovation and rapid acceleration of globalization, defined as the increased movement of people, goods, and capital across nations and economies (Flyvbjerg, 2005). The digital transformation and the expansion of knowledge have profoundly changed how we live, learn, work, and interact. These social and economic structural changes have significant implications for education and the workplace, from transforming instruction to increasing student mobility to shifting the marketplace for talent and skills from a local stage to a global one.

These transformations have implications for the role of education and the importance of investing in education and skill training. Given the benefits of education, human capital for the twenty-first century incorporates accessible digital technology-centered education as the foundation for individual development and economic growth. However, fundamental changes in education are required to implement this concept of human capital, such as integrating digital-skills training and soft-skills development with innovations to expand training options and modalities. In Africa, human capital development in the twenty-first century involves maintaining primary and secondary level funding while improving tertiary level capacity to incorporate technology and accommodate the youth bulge and working adults. This shift in education policy and investment responds to globalization and digital transformation and is based on human capital theory relevant to the twenty-first century.

Human capital

Physical capital vs. human capital

The extended description of human capital is defined as

> "intangible collective resources possessed by individuals…[which] include all the knowledge, talents, skills, abilities, experience, intelligence, training, judgment, and wisdom possessed individually and collectively, the cumulative total of which represents a form of wealth available to nations and organizations to accomplish their goals.
>
> Human capital is available to generate material wealth for an economy or a private firm. In a public organization, human capital is available as a resource to provide for the public welfare. How human capital is developed and managed may be one of the most important determinants of economic and organizational performance" (Huff, n. d.).

Physical capital is defined as physical assets such as land, equipment, and buildings. A country's physical capital consists of financial, fixed assets such as durable, fixed, and reproducible assets (Huff, n. d.).

In the global debate over how to stimulate economic growth and development, there has long been a divergence of opinion over whether to prioritize physical infrastructure, human capital development, or a business-friendly climate. Former World Bank President Kim recently wrote, "[g]overnments in pursuit of economic growth love to invest in physical capital—new roads, beautiful bridges, gleaming airports, and other infrastructure" (Kim, 2018). President Kim alluded to the World Bank's position on the importance of large-scale infrastructure projects in development policy. The policy stated advanced developing economies needed to increase exports and expand light manufacturing for economic growth. Therefore, physical capital should be the focus of investment rather than human capital. For more than a half-century, the focus of investment to spur economic growth was on large infrastructure projects to build physical capital, delivering painful lessons about the consequences of systems that fail to invest in people.

Large-scale infrastructure projects, however, are inherently complex and risky, necessitating extensive stakeholder consultation, accurate costs, sober and realistic forecasts, and, most importantly, decision-makers' impartiality. Several studies investigated the underlying challenges of this policy position and in completing large-scale projects. The studies found issues such as competing interests of various actors, deliberate distortion of cost-benefit analyses, and strategic false representation, which frequently resulted in the selection of the least qualified implementer, resulting in significant cost overruns and shortfalls (Altshuler & Luberoff, 2003; Flybjerg et al., 2004; Flyvbjerg, 2005; Morris & Hough, 1987; Priemus, 2007). Consequently, numerous projects were abandoned during the era of large-scale infrastructure development in Africa, and those completed only rarely benefited residents.

These costly infrastructure projects were dubbed “white elephant projects.”[13] due to their widespread failure (Robinson & Torvik, 2005). However, governments were still obligated to repay loans whether the projects were finished or abandoned. The cost and focus on this development strategy led to a significant cutback in health and education, particularly tertiary education (*Infrastructure Finance*, 2022). Furthermore, since these expansion plans did not require a skilled workforce, educational policy focused on basic literacy and numeracy, effectively abandoning higher education in Africa.

The digital transformation and experience from past decades’ have shifted the debate on economic growth strategies and goals away from physical capital and toward human capital. The evolving consensus appears to hold previous growth strategies and investments were “a mistake, because neglecting investments in human capital can dramatically weaken a country’s competitiveness in a rapidly changing world, one in which economies need ever-increasing amounts of talent to sustain growth” (Kim, 2018). This revision was in response to the post-industrial economy, which has reinforced the importance of investing in human capital through education as essential for the digital transformation era, where knowledge and skills are required for economic growth.

Human Capital Theory

Human capital theory is a centuries-old concept that argues the knowledge, skills, abilities, and aptitudes a person accumulates constitutes a type of capital. Human capital theory advances these skills and knowledge are assets that can be measured and have economic value (Becker,

[13] White elephant projects are “investment projects with negative social surplus” where “cost benefit calculations were ignored and inefficient investment projects undertaken” (Robinson & Torvik, 2005).

1993; Lutza et al., 2019; Schultz, 1961; Sen, 1999; Smith, 1863). Prior to Becker and Schultz, economists largely conceived of capital in terms of physical assets such as factories and land, with little attention to the contributions of workers, who were simply labeled as skilled or unskilled. Schultz (1961) states, “I propose to treat education as an investment in man and to treat its consequences as a form of capital...I shall refer to it as human capital” (p. 571). This concept can be traced back to Adam Smith and is continued in Becker’s (1993) work on wage analysis and Sen’s (1999) work on capabilities.

Early Human Capital Theory

The genesis of the principles of human capital theory is in two influential works of Adam Smith, The *Theory of Moral Sentiments* (Smith, 1863) and *The Wealth of Nations* (Smith, 1776). They constitute the foundation of the twin thread of human capital theory, the investment, and benefit of education at the individual and community levels. *Moral Sentiments* (1863), a thesis on human social interaction, claims individuals make decisions based on self-interest, broadly defined to encompass sympathy and empathy, which can be understood as ‘do no harm’. Smith acknowledges individuals have selfish desires which must be curbed for people to live in social harmony. Society safeguards collective security through “justice,” an external, public system that ensures safety and order, while individuals practice “beneficence,” an informal arrangement in which individuals self-moderate and practice empathy based on personal judgment for the benefit of social cohesion (Smith, 1863). The value of education is it enables individuals to develop the ability to manage selfish desires, broaden perspectives, and develop better judgment to exercise beneficence. Smith (1863) believed these outcomes of education serve society and the individual by releasing individuals from superstition and other vices, which ultimately contribute to the general welfare of society.

The Wealth of Nations (1776) likewise stresses the benefits of education and explicitly tackles the role of the state in education provision. Smith argues education for children should be accessible and affordable, and in cases of impoverished families, the state should subsidize access (Smith, 1776). With respect to adults and workers, society has a vested interest in providing lifelong education to counteract alienation from menial labor. Smith (1776) considers the effect of repetitious factory work in demoralizing the workforce, thus alienating them from society:

> "The man whose whole life is spent in performing a few simple operations…has no occasion to exert his understanding, or to exercise his invention, in finding out expedients for removing difficulties which never occur. He naturally loses, therefore, the habit of such exertion, and generally becomes as stupid and ignorant as it is possible for a human creature to become. The torpor of his mind renders him not only incapable of relishing or bearing a part in any rational conversation, but of conceiving any generous, noble, or tender sentiment, and consequently of forming any just judgment concerning many even of the ordinary duties of private life. Of the great and extensive interests of his country, he is altogether incapable of judging; and unless very particular pains have been taken to render him otherwise, he is equally incapable of defending his country in war. The uniformity of his stationary life naturally corrupts the courage of his mind, and makes him regard with abhorrence the irregular, uncertain, and adventurous life of a soldier. It corrupts even the activity of his body, and renders him incapable of exerting his strength with vigor and perseverance, in any other employment

> than that to which he has been bred. His dexterity at his own particular trade seems, in this manner, to be acquired at the expense of his intellectual, social, and martial virtues" (Smith, 1776, p. 603).

Smith also promotes skill training as essential for workers to obtain specialized skills. This specialization reduces the alienation of repetitive work and allows for a division of labor, allowing for a more efficient production model. Moreover, specialized workers acquire a competitive advantage in employment and negotiating compensation, whereas manufacturers boost productivity, resulting in economic growth.

Smith also introduces the concept of human capital accumulation through a discussion of the wage differential between skilled and unskilled workers and defining human capital investment as, "[one was] educated at the expence of much labour and time to any of those employments which require extraordinary dexterity and skill." (Smith, 1776). He identified individuals' investments in skill acquisition as both capital and competitive advantage. Skilled workers had higher productivity and were thus in demand in the workforce, giving them bargaining power in wage negotiations.

Twentieth-century human capital

The twentieth century saw human capital theory modeled as an economic instrument rather than one centered on people. As such, economic indicators tracked progress and economic growth with little regard for aspects that contributed to individual well-being. However, human capital theory from its inception, was a framework for investment in people. Shultz (1961) and Becker (1993) focused on education as a human capital investment that produces capital and other output that benefits society, the individual, and the economy. Even though human capital theory encompasses all types of investments in individuals, from health to education, a substantial portion of the literature concentrates on education. This disproportionate focus was due, first, to the impact of education on individual and community health and, second, to the ease in quantifying the benefits of education in terms of earnings, specifically the ability to conduct an empirical analysis of the relationship between education level and income (Sweetland, 1996).

Shultz (1961) notes, "[e]cominists have long known that people are an important part of the wealth of nations" (Schultz, 1961, p. 2). He observes in Western Europe and the US, human capital was growing at a faster rate than "conventional (nonhuman)" and has contributed to "national output" higher than the "increase of land, man-hours, and physical reproducible capital" (Schultz, 1961, p. 1). Schultz acknowledged reducing people to capital could be interpreted as treating individuals as goods and commodities. He elaborates on his theory by referencing Adam Smith's works, which previously suggested that an individual's skills and abilities form capital. He also cites income discrepancies between farm-based and urban workers, those in the US South and the US North, and young workers vs. older workers to demonstrate the economic growth that arises from human capital. In his analysis, the level of education and training appeared to be the distinguishing element in the wage discrepancies between the groups above, with urban workers being more skilled than their rural counterparts and younger workers obtaining more years of education than older workers.

Schultz's (1961) discussion of the need for human capital for economic progress contains some key observations on the misguided focus of investment in developing countries:

> I have been impressed by repeatedly expressed judgments, especially by those who have a responsibility in making capital available to poor countries, about the low rate at which these countries can absorb additional capital. New capital from outside can be put to good use, it is said, only when it is added "slowly

> and gradually." But this experience is at variance with the widely held impression that countries are poor fundamentally because they are starved for capital and that additional capital is truly the key to their more rapid economic growth. The reconciliation is again, I believe, to be found in emphasis on particular forms of capital. *The new capital available to these countries from outside as a rule goes into the formation of structures, equipment and sometimes also into inventories. But it is generally not available for additional investment in man.* Consequently, human capabilities do not stay abreast of physical capital, and they do become limiting factors in economic growth. It should come as no surprise, therefore, that the absorption rate of capital to augment only particular nonhuman resources is necessarily low. The Horvat formulation of the optimum rate of investment which treats knowledge and skill as a critical investment variable in determining the rate of economic growth is both relevant and important (Schultz, 1961, p. 7).

Individuals significantly contribute to economic growth since their accumulated capital, in the form of knowledge and skills, is the source of increased productivity. Without investment in education and training, the cornerstone of human capital, the efficiency and productivity required for growth and development cannot be attained.

Schultz (1961) underscored his thesis on education's contribution to human capital development by reiterating it was intended to supplement, rather than replace, education's social and cultural purposes. He argues, "in addition to achieving these cultural goals, some kinds of education may improve the capabilities of a people as they work and manage their affairs and that these improvements may increase the national income" (Schultz, 1961, p. 572). He added increasing investment in human capital yields improved quality of work through efficiency and innovation, thereby spurring economic growth. Even as the value of goods to income tends to decline, human capital relative to income rises due to the demand for skills and abilities (Schultz, 1961). Furthermore, because of human capital investment, intangible benefits, such as psychological and emotional well-being, that reduce criminality and isolation accrue to the individual, family, community, and economy.

Becker (1993) developed a framework for an empirical analysis of individual investment behavior to assess human capital theory. Becker, like Schultz, defined human capital as the skills and knowledge that an individual accumulates and concluded economic growth is directly related to the intensity and quality of investment in the individual (Becker, 1993, p. 3). Becker (Becker, 2002) presented human capital in education taking place in several settings, formal education, such as high school and college, and informal such as on-the-job training. He differentiates between economic assets such as stocks and factories that “yield income” and assets (capital) accrued by individuals from education and training (Becker, 1993, p. 15). He further elaborates, per the concept of capital, expenditures in education are an investment that yields human capital “because people cannot be separated from their knowledge, skills, health, or values in the way they can be separated from their financial and physical assets” (Becker, 1993, p. 16).

While working at the National Bureau of Economic Research (NBER) in the late 1950s, Becker applied economic theory (neoclassical price theory) to the rate of return on different levels of education (Teixeira, 2014). Eventually, Becker (1993) developed an empirical analysis framework of human capital that examined the effect of formal education on individual earnings and national productivity, which he referred to as private and social rates of return on capital accumulation, i.e., education and training. The model incorporated state investment in education, such as schools and instructors, and individual investment in education, such as foregone income during training and educational expenses. Becker (1993) found the rate of return for college and high school education was 13%-28%. He also discovered older workers with a college education or higher had higher earnings. Due to incurred educational costs, younger college graduates had income comparable to that of high school graduates, but their income increased over time as educational costs were fully recovered (Becker, 1993). Becker's study forms the foundation of education economics and other rate-of-return models and analyses.

Moreover, Becker contributed to Human Capital theory by bridging the gap between human capital and technology. Becker (1993) observed the evolution of technology and the changes it brought to education from the mid to late twentieth century. Young people were encouraged to study education beyond high school because "relatively unskilled and uneducated persons [were] becoming increasingly obsolete in the American economy" due to advancements in technology in society and the workplace (Becker, 1993, p. 219). He uses the evolution in agriculture to illustrate the link between education and technology:

> "Education is of little use in traditional agriculture because farming methods and knowledge are then readily passed on from parents to children. Farmers in countries with traditional economies are among the least educated members of the labor force. By contrast, modern farmers must deal with hybrids, breeding methods, fertilizers, complicated equipment, and intricate futures markets for commodities. Education is of great value since it helps farmers adapt more quickly to new hybrids and other new technologies. Therefore, it is no surprise that farmers are about as well educated as industrial workers in modern economies" (Becker, 1993, p. 25).

Therefore, the level of technical innovation in the economy is a key determinant of whether initial investments in human capital stagnate at low-income levels or yield continued productivity.

Becker (1993) frames on-the-job training as an essential human capital accelerator with implications for personal earnings and productivity. He distinguishes between specific training, which improves workers' skills in company-specific areas, and general training, which provides skills that can be applied more broadly. Using statical analysis, Becker shows companies with general training programs had marginal productivity, while individuals in training gained mobility to seek higher income due to the transferability of the training. Whereas specific training increases firm productivity within the company, it does not always translate into higher wages and mobility for workers due to the limited transferability of the training (Becker, 1993). His research also demonstrates training has a higher impact on younger workers' productivity and earnings than older workers. However, companies that do not offer on-the-job training face limited availability of skillsets, thus, most tend to offer a blend of general and specific to remain competitive and retain talent.

However, Becker's empirical study is limited because non-whites, women, and immigrants had fewer rights and opportunities than white men. It is important to note that these findings apply to only white men since the study found lower educational attainment and earnings for non-white men and all women. Becker (1993) attributes this to a difference in opportunities resulting from a lack of funding, discrimination, and other forms of bias. Furthermore, other issues, such as the quality of schooling and "differences in terms of personal traits, such as ability and socio-economic factors," though of concern, were not captured in the framework (Teixeira, 2014, p. 12).

Human capital and technology

The importance of human capital investment as a driver of technology and innovation was recognized by Smith, Schultz, and Becker. Smith (1776) identified the implication of the Industrial Revolution and subsequent task-level labor modification due to automation as early as the 18th century. He noted the increase in the division of labor between unskilled "labour that can be performed without first acquiring specific skills by way of education or professional training, apprenticeship, or learning-by-doing" and skilled "skills acquired through formal education and experience (Brugger & Gehrke, 2018, p. 666). In contrast to the agrarian period, the industrial era was based on manufacturing and automation, fueled by ongoing innovations in existing systems to increase productivity and a division of labor between workers and management. Therefore, those with the training and skill sets to engineer innovations and oversee operations fared well and benefited from the changes during the period.

Becker builds on Smith's observation to address the relationship between human capital and technological advancement by underscoring the "synergies between new knowledge and human capital" (Becker, 2002). He draws attention to the links between an increase in the number of educated people and an increase in technological and scientific innovations. Moreover, the expansion of technology improves efficiencies and "raises the productivity of labor" while adding to the value of education (Becker, 2002).

This link between technology and education is essential in the twenty-first century as "technological progress raises the demand for skills, and human investment slake that demand" (Acemoglu & Autor, 2012, p. 428). Increasing the intensity and quality of human capital investment in education provides a platform for talented individuals to transform processes and technology, resulting in innovation. As the education and skill level in the workforce increase, the ease of adapting innovations rises along with growth in productivity. The economic significance of the relationship between education and innovation is demonstrated by the performance of East Asian countries in the 1990s and, more persuasively, by the current pace of digital transformation and economic growth in African countries leveraging digital and scientific innovations.

Human capital and Neoliberalism

Human capital became associated with economic metrics such as GDP in the late twentieth century, mainly owing to the ascendancy of neoliberal ideology and policy in the 1980s. For this study, Neoliberalism is defined as an economic theory that advocates a reduced role of government to increase competition. It advocates for liberalization of markets and trade, privatization, and deregulation. The neoliberal development theory deems capitalism as the engine of development. It espouses removing obstacles to trade and investment and decreasing public spending such as education, health, and social welfare. However, neoliberal economic theory has increasingly been scrutinized for its failure to deliver on the promise of prosperity for all, driven by the free market. Nobel Laureate economist Stiglitz declares the failure of Neoliberalism in the twenty-first century is evident in the lack of resilience and security in the world today, where economic markets have become ungovernable, wages are down, growth is lower than at any point in history, wealth is concentrated, and safety nets have disappeared (J. Stiglitz, 2022; J. E. Stiglitz, 2019). In the development sector, the neoliberal development strategy has not delivered on development but has instead expanded inequality, 'marketized' the public sector, and weakened the African political economy (Ayelazuno, 2014; Caffentzis, 2002; Dutta et al., 2022; Ostry et al., 2016; Zenawi, 2011).

Neoliberal as an economic model is often associated with cutting tariffs and taxes, deregulation, a push for privatization, cutting public expenditures in social welfare such as education and health, and emphasis on individual responsibility as opposed to the public good (Biebricher, 2018; Kuttner, 2019; Thorsen & Lie, 2007). The earlier Keynesian economic model promoted education as a means of improving the "quality of capital and labour" and as a mechanism for "ensuring that all members of society were able to participate and contribute" to economic growth (Davies & Bansel, 2007, p. 254). However, beginning in the 1980s, with the development of neoliberal policy, education was transformed into a commodity "inextricably mired in the capitalist relations of the market economy and capitalist labor market" (Willis, 2004, p. 193). Therefore, following the neoliberal model, the primary driver of education policy was privatization and limiting public expenditures in public education, particularly in Africa.

Neoliberal policies analyzed human capital as a largely nation-state-driven framework focusing on economic measurements like GDP rather than a global holistic assessment that included well-being and the value of an individual's capabilities leveraged in the workforce. In this climate, human capital theory was an economic model focused on maximum utility as a driver of educational investment (Sen, 1999). As a result, policy recommendations included reducing public funding for education, focusing more on the rate of return, and encouraging privatization as a substitute for government spending.

This shift in education policy is particularly noticeable in Africa, where neoliberal strategies such as privatization, maximum utility, and rate of return models for education investment have been promoted (Alexander, 2001). As noted earlier, World Bank education policy for Africa was based on these neoliberal instruments, such as the rate of return and recommended remedies advanced by neoliberal economic theory. Moreover, with the enforcement mechanisms such as aid conditionality and Structural Adjustment Programs (SAP), education policy in the latter half of the twentieth century concentrated on cutting public sector education expenditures, notably at the tertiary level, in favor of loan financing for these activities. At the time, the debate on educational investment was whether economic development was required before investing in human capital or whether investing in humans resulted in economic development.

Several scholars have sought to weigh in on the debate to illustrate the impact of human capital investment on economic growth. A quantitative analysis of the relationship between human capital investment and economic and social development discovered a strong, positively correlated link of r=+0.994 with a p-value of 0 (Lonska & Mietule, 2015). Furthermore, while increased human capital investment led to higher economic growth, even modest investments led to progress; thus, low-performing economies could still benefit from educational investment, albeit at a lower level. Furthermore, “enhancement of the developed human capital”, defined as higher quality and intensity in educational investments, “contributed to transformation process of ‘resources economy’ turning into a ‘knowledge economy’” (Lonska & Mietule, 2015). Therefore, regardless of the level of investment, education tends to yield benefits; however, overall restructuring of an economy into one aligned with the twenty-first century requires additional investment in quality improvement and increasing access.

Human capital and public economics

Amartya Sen, a Nobel Laureate in welfare economics, argued human capital development was a tool for developing capabilities that enabled people to not only participate in the workforce but also realize essential freedoms that allowed individuals to live lives they value. Sen (1999) proposed a concept of development challenging the prevailing neoliberal perspective and went beyond economic measures, in which people were not at the service of economic growth but rather the other way around, and defining development as “a process of expanding the real freedoms that people enjoy” and the growth as an instrument for doing so (Sen, 1999, p. 3). This reorientation broadens the analysis of development effectiveness, beyond data and metrics such as income and symbolic rights and justice, to evaluating society’s achievement based on the individual freedom its members enjoy.

The goal of development is the expansion of individual freedom, where development removes “major sources of unfreedom: poverty as well as tyranny, poor economic opportunities as well as systemic social deprivation, neglect of public facilities as well as intolerance and overactivity of repressive states” (Sen, 1999, p. 3). However, freedom depends on several social and economic factors, the most important of which is education, which frees individuals from poverty and oppression and allows them to participate in public debate and the economy. Therefore, development is more than just a goal. It is also a means of realizing individual freedom through two pillars: procedure (the ability to participate in a democratic process) and opportunity (the availability of economic and social pathways to achieve freedom from deprivation).

According to Sen (1999), freedom is intimately tied to development because obtaining it requires individuals’ free will and participation, and second, the state of unfreedom is a stronger indication of poverty than GDP. Development must be evaluated through the lens of the individual because economic indicators are limited and do not account for individuals’ substantive freedoms. Freedom is classified between substantive freedoms, widely defined as freedoms that allow individuals to live full lives, and instrumental freedoms, which are interconnected freedoms that determine whether an individual fulfills their potential. Instrumental freedoms include essential conditions such as political freedom, economic facilities, social opportunities, transparency, and security, that create "condition of good health, fundamental education, and the encouragement and cultivation of initiatives" (Sen, 1999, p. 5).

Education is a vital instrumental freedom contributing directly to the "freedom people have to live the way they would like to live" (Sen, 1999, p. 38). Literacy and numeracy are essential for acquiring health information, increasing communication opportunities in society, and allowing participation in public life. The indispensable role of education as a facilitator of freedom has been demonstrated in several studies found educational attainment is associated with general health improvement, increased life expectancy, higher income, and overall improved quality of life, including material, emotional, and social well-being (Edgerton et al., 2012; Luy et al., 2019; Powdthavee et al., 2015). As such, education can be viewed as a "social opportunity," as a public good that influences substantive freedom that develops an individual's capabilities, like freedom *from* deprivations such as poverty and illiteracy and freedom to "lead lives—that they have reason to value" (Sen, 1999, p. 85).

Sen's main point in the concept of development as a tool for freedom is centered on the need for individuals to develop their capabilities to achieve full freedom to live lives they value. Sen's (1999) development thesis, the concept of capacities as a tool for liberty and development, is related to previous human capital theory positions. Smith, Schultz, and Becker perceived education as an investment in expanding an individual's overall life options, yielding economic growth. Investment in education can "enlarge the range of choice available…[and] is one way free men can enhance their welfare" (Schultz, 1961, p. 2). Individuals are agents of growth in human capital as they're the instrument and vehicle of social and economic development. Therefore, human capital can be understood as, first and foremost, developing individual capabilities to achieve freedom and, second, as a strategy for increasing productivity and economic growth.

Human capital and gender

As an economic concept, human capital theory has far-reaching implications for how gender, education, employment, and economic outcomes interact. Education and skill acquisition influence individual development and economic growth; however, women and girls have faced considerable impediments to accessing education and economic advancement opportunities. Women are sometimes expected to prioritize family responsibilities above education and professional progress, limiting their ability to invest in human capital. Furthermore, human capital is also developed through labor-market skills and experience, however, women confront obstacles to employment and advancement, particularly in male-dominated industries where they experience prejudice or bias. These gender-based economic disparities substantially limit girls' and women's prospects and place them at a distinct disadvantage.

One of the shortcomings of early human capital theory is the omission of women's labor and gender disparities in terms of equal access to human capital accumulation pathways such as education. Although Smith refers to the difference between men and women in social and familial contexts, he does not bring the depth of his treatment of social and economic realms discussions to the analysis of gender differences of his time. Smith (1863) raises gender in the context of propriety, a component of the sympathy framework, and the basis of what he considered appropriate behavior for men and women. Smith, for example, delves into the gender divide by characterizing women as the "fair sex" who exhibit "tenderness" and are "equated to 'men of weak nerves'...not well equipped to public and commercial life, which requires high degrees of generosity, prudence, and self-command" (Nerozzi & Nuti, 2011, p. 16). He does not, however, extend his observations to other places where men and women were valued and existed in very different ways.

Moreover, although Smith advocates public education in *Wealth of Nations*, he accepts women's lack of access without question and writes:

> "there is accordingly nothing useless, absurd, or fantastical, in the common course of their education. They are taught what their parents or guardians judge it necessary or useful for them to learn, and they are taught nothing else. Every part of their education tends evidently to some useful purpose; either to improve the natural attractions of their person, or to form their mind to reserve, to modesty, to chastity, and to economy; to render them both likely to became the mistresses of a family, and to behave properly when they have become such. In every part of her life, a woman feels some conveniency or advantage from every part of her education. It seldom happens that a man, in any part of his life, derives any conveniency or advantage from some of the most laborious and troublesome parts of his education" (Smith, 1776, p. 574).

The Industrial Revolution was in full swing at this point, and women were in the workforce, therefore, the omission of discussion of women's paid labor is notable. Furthermore, Smith was writing on the competitive advantage of nations at a time when the wage disparity between men and women was between one-third and two-thirds (Burnette, 1997). What little mention of women's labor can be found was limited to what he classified as unproductive labor, such as childbearing, raising, and housework, which essentially "prevented women from being considered relevant for the development of capitalism, reinforcing their social dependence on men at a time when their participation in the labor force could have allowed a substantial bettering of their condition" (Nerozzi & Nuti, 2011, p. 14).

Gender roles eventually entered the human capital discussion with Schultz's study of the role of the family in economic growth, which addressed traditional gender norms and social expectations that limit women's economic advancement opportunities. He discusses the importance of family as a critical source of human capital investment, providing resources such as time, money, and emotional support to help individuals develop their skills and abilities (Schultz, 1974). However, he points out traditional gender roles and expectations, on the other hand, can limit women's ability to invest in their education and training, as they are frequently expected to prioritize domestic responsibilities over education and career advancement.

Becker (1993) expands on Schultz's work by linking educational opportunities to workforce composition. Becker followed his brief overview of gender bias and prejudice in human capital with a detailed examination of labor market discrimination, such as wage differentials, occupational segregation, and the function of social norms and cultural expectations in shaping gender roles and opportunities in the labor market. *The Economics of Discrimination* (1971) delves deeper into workforce discrimination driven by prejudice and market forces. In *Human Capital, Effort, and the Sexual Division of Labor* (1985), he looked into the sexual division of labor, specifically the effect of women's disproportionate responsibility for childcare and housework, notably married women, on their earnings and professional opportunities. Becker (1985) observes that while women's labor force participation has increased due to fertility, divorce, and other factors, the persistence of traditional sexual divisions of labor has meant that "housework responsibilities lower earnings and affect the jobs of married women by reducing their time in the labor force and discouraging their investment in market human capital" (Becker, 1985, p. S55).

Gender is carefully considered in Sen's (1999) thesis on human capital by situating gender as a significant component of his discourse on freedom. Sen takes a clear and practical approach to understanding the role of gender in development, stating gender equality is a prerequisite for achieving sustainable and inclusive development. Gender inequality "afflicts—and sometime prematurely ends—the lives of millions of women, and, in different ways, severely restricts the substantive freedoms that women enjoy" (Sen, 1999, p. 15). He asserts development cannot be considered thoroughly free if half of the population, specifically women, are denied access to resources allowing the development of their capabilities and achieving complete freedom. He contends gender inequality stifles economic growth, wasting women's potential contribution.

Sen (1999) highlights education access as an area where gender inequality impedes development. Limiting girls' and women's education is a fundamental denial of their freedom and ability to develop capabilities and opportunities. Women's capabilities and freedoms are restricted because of gender inequality, perpetuating a cycle of poverty and underdevelopment. Gender discrimination also has a negative social impact, contributing to poverty, illiteracy, and infant mortality. Therefore, for Sen (1999), investment in girls' education, access to reproductive health care, and legal reforms are critical policy tools for combating gender discrimination and violence. He also advocates for policies promoting gender equality, women's empowerment in the political sphere, decision-making processes, and equal pay.

Although the human capital field has been slow to consider gender disparities in access to essential human capital development tools, recent literature has attempted to feature the barriers and challenges faced by women. Research reveals gender discrimination in human capital is costly and does not only affect women but also society and the economy. Limiting the capabilities of talented girls and women inhibits economic progress by reducing production and advancing unqualified boys and men who may not perform at the desired level. For developing economies, gender gaps in human capital have been shown to impact overall national well-being and growth noticeably. Therefore, gender equity is essential to human capital development, as demonstrated by the treatment of gender disparities in areas such as access to education, equality in employment, and the gender wage gap, in recent literature.

Conceptual framework

Human capital for the twenty-first century

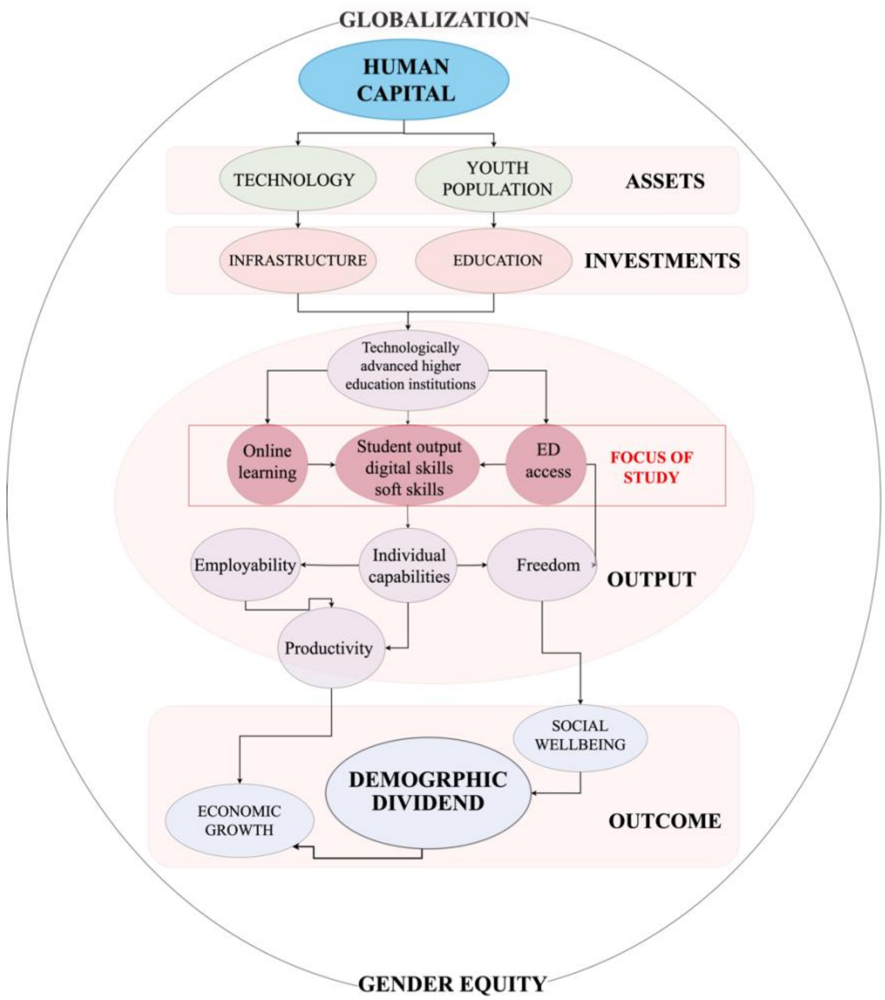
Human capital in the twenty-first century is defined in the African context by digital transformation and demographic dividend, both of which have the potential to accelerate and diffuse individual freedom and economic progress. A human capital development strategy for the twenty-first century is founded on the premise people are the target of investment, technology integration promotes digital skills and expanded access accelerates education and training *(see Figure 4).* This framework builds on the essential elements of human capital theory while shifting strategies to reap the benefits of digital and demographic dividends.

Figure 4 depicts how education and digital technology interact to maximize the demographic dividend. It located the study within this larger framework for human capital development in the context of globalization and gender equity. The available assets, youth population, and technology build on investments in infrastructure and education to create a sequence of outputs. In terms of education, it yields technologically advanced tertiary institutions that increase access through online learning. It provides digital skills training to enhance individuals' capabilities, preparing them for employment and entrepreneurship, ultimately leading to personal fulfillment and freedom. This investment leads to increased productivity, economic growth, and general social well-being, all contributing to capturing the demographic dividend. The framework considered several factors, including the need to improve educational investment, the intersection of technology and education, lifelong learning, and the increasing mobility of workers.

Intensified educational investment

Increasing the intensity of educational investment is critical in this knowledge and information based economy (Becker, 1993; Lonska & Mietule, 2015). The core principles of human capital theory are, first, individuals accumulate knowledge, skills, and capabilities benefit the individual and have economic value. Second, education is a vehicle for accruing said capital. The thread of these central tenets has gradually spread to even traditionally neoliberal institutions, where the policy of prioritizing infrastructure investment and economic austerity has given way to a discussion on human capital investment. This reversal was evident when the World Bank made human capital the central theme of its 2018 Spring meetings and announced a new annual human capital index (Kim, 2018). The index is part of a Human Capital Project, "a global effort to accelerate more and better investment in people for greater equity and economic growth" (The World Bank, 2023). The index attempts to quantify the impact of such investment on economic growth. This new index joins other reports that track social rather than economic progress, such as the United Nations Human Development Report and World Happiness Report. This trend is significant as it represents a shift from emphasizing physical capital to recognizing human capital as essential to economic growth.

Figure 4: Conceptual Framework



Technology

The global economy has entered a post-industrial phase in which people, rather than machines, drive production and productivity. This shift from manufacturing to automation has increased productivity while emphasizing the link between education and technical skills (Bank/IFC, 2019). According to Becker (1993), the intensity of educational investment results in higher-quality human capital development, which supports greater innovation.

Furthermore, the interaction between education and innovation, in which automation and digital technology necessitate skilled workers, who in turn drive innovations, demonstrated a direct relationship between technology, innovation, and education (Becker, 1993; Mariz-Perez et al., 2012; Romer, 1989; Teixeira, 2014). The education technology nexus was recently highlighted in the 2019 World Development Report, which profiled the role of technology in quality human capital development and advocated for increased investments in education and training.

Finally, digital technology is also vital in delivering education as a mechanism for increasing access to intensify education investment. Incorporating technology into instruction serves the dual purpose of improving educational access while developing students' digital skills, enabling active and constructive engagement in an increasingly technological world (UNESCO, 2019). Hence, human capital for the twenty-first century is cultivated through education and focused on individual well-being and productivity responsive to the mobility and adaptability of globalization and the digital revolution.

Lifelong learning

Human capital development in the era of digital technology includes life-long learning. The pace of digital transformation and people's extended work life makes lifelong learning an essential component of human capital development in education. Becker's (1985) discussion of training can be understood as life-long learning as a necessary part of human capital development in the twenty-first century. Lifelong learning is critical in the post-industrial economy, where jobs and tasks are constantly changing due to the rapidly evolving workplace. Hence, expanding on Becker's (1993) general training model where transferable skills enable worker mobility and adaptation to keep abreast of the rapid change in the workplace.

Moreover, the accelerated pace of technology "mean[s] that the knowledge that people acquire in school is becoming obsolete more quickly than before" (The Economist, 2007). Short-term training and certification are becoming more popular as individuals add specializations to reflect changes in their industry and, in some cases, move to emerging areas of the economy. Similarly, skilled individuals drive innovation through extended learning and training, providing them with the advanced knowledge required to engage in and innovate their tasks. When combined with higher life expectancy, which extends individuals' working lives, the demand for lifelong learning is an enduring feature of the post-industrial economy. Therefore, life-long learning, as articulated in the works of Smith (1863) and Becker (1993), is essential for individual growth and technological innovations regardless of the sector in the context of twenty-first-century human capital.

Professional nomads

Unlike previous generations, where people stayed in jobs for their entire lives, today's workforce is characterized by mobile workers with broad skill sets, such as digital and analytical, complemented by a core competency. Becker's example of farm workers can be extrapolated to other professions where the skills demand beyond core competency has increased with innovation and integration of technology. A report by the World Bank noted, "[t]he shifting frontier for skills is essential context for the current discussion on human capital" (IFC/The World Bank, 2019, p. 20). Rapid technological changes have shifted the focus of a well-educated worker in the twenty-first century from qualifications required for a lifetime job to skills needed to do specific tasks in constantly changing jobs. The days of education and training focusing on a single set of skills that would allow a worker to pursue a career in a specific field with minimal changes are long gone, giving way to a landscape of mobile employment and lifelong learning. Today's workplace is in constant flux, with jobs disappearing and being replaced by jobs requiring different skill sets.

Demographic dividend

The African youth population is another dimension of the human capital development for the twenty-first century discourse. Previous models that linked demographic dividend to an increase in the working-age population for economic growth no longer hold true in the information and knowledge economy (Lutza et al., 2019; Romer, 1989). Recent studies discussed earlier have demonstrated the benefit of population growth is accrued from the rise in the number of educated individuals participating in the economy and not increasing the working-age population (Lutza et al., 2019). In this age of technology-driven efficiency, improved access is critical for a demographic dividend, and countries with higher levels of well-educated populations will benefit the most (Romer, 1989).

Summary

This chapter discussed the study's conceptual framework, a reconceptualization of human capital theory in the context of the knowledge economy, lifelong learning, and the African demographic dividend. Human capital in the twenty-first century is cultivated through investment in education, allowing individuals to accumulate capital, which benefits both the individual through increased income and society by constructing and preserving social cohesion, providing economies with a competitive advantage.

In many ways, human capital for the twenty-first century is a return to the fundamental principles of education as a benefit to the individual and society, an engine for economic competitiveness, and essential for a person's freedom from poverty, with a caveat on the central role of technology and the urgency in reaping the benefits of demographic dividend. This takes place by moving away from economic metrics such as GDP and returning to centering the individual and the value of education, technology, and mobility for both the individual and the economy. This requires sustaining investment at the primary and secondary levels within the African context and increasing enrollment capacity at the tertiary level. This transformation responds to globalization and digital innovations, aligning the theory with the twenty-first century.

Digital transformation has invariably altered society and the economy over the last quarter-century, resulting in seismic shifts in the workplace and education. Therefore, in the context of Africa's current digital innovation and demographic dividend, quality education is essential for individuals to develop capabilities that allow them to live a life they value and effectively participate in economic activities. Furthermore, advances in technology have altered not only the nature of work at the functional and task levels but also the form and mode of education delivery. Thus, the pressing challenge for educational institutions and policymakers today is to find a way to expand access while aligning instruction with a digitized, mobile world to harness the demographic dividend and keep up with technological change. Integrating technology in education to bridge gaps in facilities and personnel offers a solution for increasing access to harness Africa's demographic dividend.

CHAPTER 4 | Methodology

Introduction

This chapter is an overview of the research context and setting, along with a discussion of the research design, research questions, methodology employed, and data analysis. The chapter begins with an overview of the institutional setting and proceeds to provide the research context. The quantitative and qualitative methods are discussed separately to maintain and highlight the study's sequential features.

Study Sites

The study aimed to provide a broad view of online learning in Africa by comparing two well-established universities in different regions of Africa with comparable online learning programs. The intent is to compare institutions across two regions to serve as proxies for similar institutions on the continent in order to capture the range of deployment strategies. The University of Ghana (UG) has an online learning program in place as well as a well-developed framework for research collaboration and IRB approval, and the study was able to navigate the process with the assistance of partners. Initially, South Africa was chosen as the second site, but the university chosen was still in the initial stages of building an online program, with just over 500 students enrolled. The search for suitable partners shifted to East Africa, Addis Ababa University (AAU), where online learning was operating across different units. With assistance from partners, the study was able to secure IRB approval, the dataset was provided shortly after. The study received IRB approval from UCLA for quantitative and qualitative studies early in the study phase.

The University of Ghana (UG) and Addis Ababa University (AAU) are the flagship national universities of Ghana and Ethiopia (see Appendix II). The similarities in situation and differences in approach offer a reasonable basis for comparison. Although they have implemented educational technology and online learning in diverse ways, the two countries have a long history of adult education goals that are the basis for distance learning today. Since their foundation, UG and AAU have offered adult education in some capacity which evolved into distance learning. The resulting difference in online learning deployment provides an opportunity to investigate two distinct approaches to the deployment of the modality in Africa.

Coastal Ghana, with a 2023 population of 34 million, and landlocked Ethiopia, with a population of 126.5 million, have distinct demographics and geography, influencing the development of higher education and Information and Communication Technology (ICT infrastructure). The contrasts between the nations give way to certain parallels in each country's flagship university has embraced online learning. Therefore, locating the research in Ghana and Ethiopia enables studying online learning in two distinct environments that reflect the range of conditions and circumstances prevalent on the African continent.

The similarities and differences between the two research sites provide a meaningful context for analyzing study sites. Although Ghana's GDP is approximately 65% of Ethiopia's GDP, the high population rate reduces the per capita GDP of Ethiopia to less than 42% of Ghana's, which has implications on government expenditures and individual spending patterns. Furthermore, variations in access, affordability, and availability of schooling, energy, and the internet are sufficiently diverse to reflect the variations observed across African nations. Additional comparative data on key indicators can be found in Appendix I.

The University of Ghana has a long history of distance learning, lending critical knowledge and experience to inform the recent deployment of online learning, which extends campus-based programs in the online modality. UG's distant education emerged from university-based adult education, which began in 1946 and was followed in 1948 by the establishment of the University College of the Gold Coast, now UG, and the Department of Extra-Mural Studies (M. A. Tagoe, 2012). The Institute of Extramural Studies, established in 1952 to house adult education at UG, was elevated to a school in 2014 with the establishment of the School of Continuing and Distance Education.[14] In the 1960s, the then Institute for Adult Education expanded part-time courses for working adults to other regions through Workers Colleges in Accra, Kumasi, Sekondi, Takoradi, and Tamale, which today comprise the UG Learning Centers (Drako, Samuel F., 1985) *(see Figure 6)*. This development was a milestone in the evolution of distance education, paving the way for correspondence courses in the 1970s, which created the groundwork for online learning in hybrid, blended, and fully online formats.

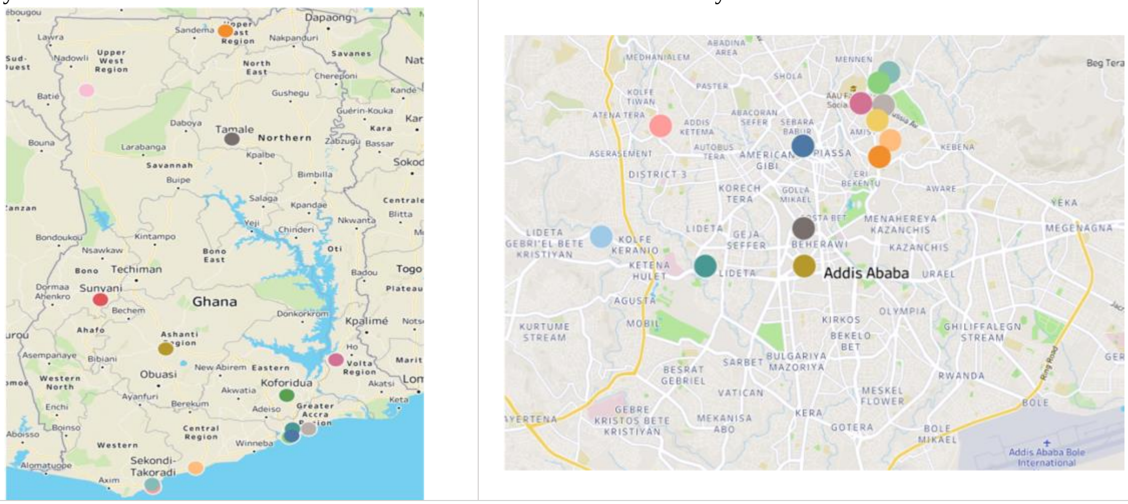
Like UG, the School of Commerce, which trained working adults, preceded Addis Ababa University's founding. Shortly after, then-Emperor Haile Selassie established the University College of Addis Ababa (1950). [15] In addition to the goal of producing a corps of well-trained professionals, continuing education for working people was an early element of the institution's courses offered through evening programs (Hapte, 1961). Since its inception, AAU has been primarily located and focused on Addis Ababa without learning outposts that characterize UG *(see Figure 5).* When the University College was renamed Addis Ababa University in 1961, continuing education was upgraded to the status of a department offering diploma and degree level education and training. There were brief periods when the Ministry of Education (MoE) mandated AAU deliver distance education across the country. However, today, the MoE and AAU offer distance education independently with distinct goals and targets. AAU's online

[14] University of Ghana School of Continuing and Distance Education https://scde.ug.edu.gh/about-us
[15] Addis Ababa University Continuing and Distance Education http://www.aau.edu.et/offices/v_president-office/office-of-the-academic-vise-president/continuing-and-distance-education-office/background/

distance education consists of a combination of stand-alone online programs offered by lecturers and departments without much central coordination.

Figure 5: Campuses and learning centers

University of Ghana	Addis Ababa University



Campus map generated in Tableau using GPS location information

Research question

The quantitative component of the study investigates the efficacy of online learning in UG and AAU to determine whether online learning has comparable outcomes to face-to-face instruction in achieving learning outcomes. To that end, this study asks:

> **Research question 1:** Is online instruction as effective as face-to-face instruction measured by Cumulative Grade Point Average (CGPA)?

The study employs a quantitative method to examine whether online instruction has a causal effect on learning outcomes as measured by Cumulative Grade Point Average (CGPA). It also looks at the demographic profile of online learning students to understand the characteristics of students likely to enroll in the modality.

The qualitative phase is a multiple case study that contextualizes quantitative data and asks:

Research question 2: How does the deployment and implementation of online learning in AAU and UG influence learning outcomes?

Through a case study of AAU and UG, the study will examine the evolution, location, and implementation of online learning and the institutional and individual challenges in its deployment.

Research design

The study's sequential mixed-method research design with quantitative and qualitative methods provides an opportunity for an in-depth, contextualized examination of online learning using various data sources (Creswell & Creswell, 2018; Ponce & Pagán-Maldonado, 2015; Schoonenboom & Johnson, 2017). A mixed method approach is a research method where qualitative and quantitative data are collected sequentially or simultaneously and integrated during analysis to yield "additional insight beyond the information provided by either the quantitative or qualitative data alone" (Creswell & Creswell, 2018, p. 41). This method presents a chance to frame results for comprehensive analysis by fusing the story of the qualitative approach with the scientific practice of quantitative research.

A mixed-method approach best serves the complexity of relationships and the relative novelty of online learning. This research strategy considers the research questions through quantitative and qualitative lenses for the multiple validities legitimation, where each technique is validated independently and together for "robust meta-inferences" (Perez, 2019). Therefore, through a mixed method design, the investigation will examine causality and elaborate and corroborate quantitative findings through a qualitative multiple case study approach for an in-depth exploration of the modality within each institution and contextualize quantitative findings.

The mixed methods approach consists of collecting qualitative and quantitative data and interpreting and synthesizing both sets of data in analysis (Schoonenboom & Johnson, 2017). Data analysis includes complementary quantitative and qualitative data analysis, which comprises "the interweaving, merging, or juxtaposition of data sources involving different types of data" (Bazeley, 2018, p. 70). Secondary data on online and face-to-face learning from UG and AAU are contextualized through interviews and focus groups. Therefore, once quantitative methods investigate whether online learning is comparable to face-to-face, the why and how are constructed and established through qualitative data.

The deployment of online learning in primarily campus-based institutions across Africa is a relatively new phenomenon. Therefore, this study is entering a relatively unexplored area, and its findings will contribute to existing knowledge to support policy and implementation. Moreover, utilizing quantitative and qualitative methods in educational research provides an opportunity to produce evidence to inform practice and policy (Walters et al., 2008). The mixed method approach allows for inclusive and cohesive investigation of online learning, contributing to the growing knowledge base focusing on the intricacies of deploying an emerging educational modality within the African context.

Quantitative

The quantitative portion is nonexperimental research based on secondary data for students enrolled in the dual-modality, online, and face-to-face programs at UG and AAU. The institutions are examined as separate cases and explored independently for comparison of online and face-to-face instruction, given differences in deployment. Causal inference is based on causal assumptions, which are the basis of randomization to ensure groups of units are comparable. These assumptions include there is only one version of the treatment (online learning), however, deployment of online learning at UG and AAU differ in terms of organizational unit, technical deployment, and levels offered, which potentially impact direct comparison across institutions. However, comparing student profiles and modalities across institutions is investigated and discussed.

The statistical analysis includes descriptive statistics examining student demographic profiles and a separate analysis of online and face-to-face students at UG and AAU. The study of the effectiveness of online learning consisted of comparing online and face-to-face instruction using causal inference through a propensity score matching procedure. The comparative analysis of the efficacy of online learning is limited to programs within each campus. It does not compare across institutions, given differences in the deployment of online learning. However, the modality's effectiveness within each institution is discussed comparatively to aid in a broader analysis and discussion of online learning in Africa.

Quantitative study sample

The sample for quantitative was limited to students enrolled in online and face-to-face instruction during the 2018-19 academic year. The COVID-19 pandemic and subsequent closure significantly disrupted education at all levels across the globe, and many institutions turned to online learning beginning the 2019-2020 academic year. The ensuing academic years are characterized by fragmented semesters, significant challenges to expanding online learning for all, and delayed academic progress. Although COVID restrictions have eased, many challenges remain. Given these circumstances, the academic year of the study sample was selected as the final year of regular instruction before COVID-19. Focusing on understanding the modality before the accelerated changes brought about by closures is an opportunity for a snapshot of online instruction before COVID-19 altered the landscape.

Furthermore, the possibility of securing datasets for fully completed courses was more likely before the academic disruption caused by COVID-19 in 2019. Since COVID-19 closures took effect during the second semester of the 2018-2019 academic year, institutions were ready to implement a plan for completing the semester through extended summer sessions. Furthermore, the number of courses delivered online increased after the spring of 2019, making it difficult to distinguish between regular online classes and courses delivered online due to COVID, inflating the institution's regular availability of online courses.

Quantitative data collection

UG and AAU have established an ethics process for conducting research, which was followed for this project. The study applied for and gained UCLA IRB approval for quantitative and qualitative studies early in the process. UCLA IRB was filed with both institutions, as was an application for institutional review. Both universities granted exemptions as the data requested was anonymized secondary data. Securing data from UG was laborious and required additional in-person and electronic follow-ups. The final dataset was delivered by UG Institutional Research approximately ten months from the Institutional Review approval date. The data request for AAU was processed in two days, and the College registrar provided the dataset two weeks later. Given the fragmented and uneven nature of data collection at the institutions, the dataset from UG and AAU did not include professional programs such as medicine, law, and engineering, which are also units that do not offer online courses or programs.

The anonymized data from UG and AAU did not contain identifiable information common to the literature on online learning. The literature on online learning posits age, employment status, learning characteristics, and previous education experiences are strong predictors of higher learning outcomes in the modality. While each institution collects various student data, only limited data points are centrally managed. Therefore, the final data set from each institution only contained narrow demographic and academic information. The shared data points across datasets include CGPA, gender, age, marital status, region, and level.

Furthermore, while each institution has a unit in charge of delivering online instruction, several units and faculty frequently offer in-person courses online during a given term without notifying the registrar or the unit tracking online instruction. These randomly offered courses are not reflected in the course listing. Hence, while it is accurate for online enrollment of courses overseen by distance learning units, it does not reflect the random online courses offered within departments at the institutions.

UG data was received as an Excel dataset with 46,092 data points of students enrolled in online and face-to-face instruction for the 2018-19 academic year: 34,918 on campus and 11,174 online. AAU data was received as three folders of several Excel workbooks covering the academic years 2018-2019 to 2020-2021. The dataset was organized across modality distance (online), evening, and regular (face-to-face). Each folder contains several Excel workbooks of enrollment in the academic unit according to terms and academic year. Each folder contains Excel files organized by division, college or school, and term. The study focused on enrollments from the 2018/2019 academic year located in the distance and regular folders with a final count of 4,051 data points, 3,36 on campus, and 1,015 online. Using *tidyverse* in *r*, each Excel term file was merged into one academic year dataset for each unit and segregated according to modality.

R is a free, open-source statistical analysis software that uses the S language, which is similar to and can be run in the R environment. R's interface is *RStudio,* an opensource software that provides an integrated development environment (IDE) for R (*R Documentation*, n.d.). The R programming language supports the development of codes to run sophisticated data manipulation and calculation operations in addition to various statistical operations. It can also code and run data visualization functions that produce plots and graphs. There are several packages that are “reproducible R codes…[including] reusable R functions, the documentation that describes how to use them, and sample data” that are freely available for download and use (*R Packages (2e)*, n. d.). R uses LaTex documentation to produce formatting and hardcopy of executed codes.

Quantitative data preparation

Data cleaning

The preliminary data cleaning process for UG data included fixing structural errors, standardizing capitalization, converting data types, modifying the class of CGPA, using the date of birth to create an age column by using the *anytime* function, checking for duplicates and irregularities, and identifying missing data. The preliminary data cleaning process for AAU data included deleting empty columns, creating new columns indicating unit, term, and modality, modifying class, using the date of birth to create an age column through the *anytime* function, and converting age and CGPA into numeric values. Finally, the two datasets consisting of face-to-face and online were merged using the *cbind* function in R to create a dataset of 2019-2018 enrollment. The AAU dataset comprised 4,051 data points, with 3,036 in campus enrollment and 1,015 in distance learning enrollment.

Following preliminary data cleaning, various R functions were applied to review datasets, including *glimpse* to view columns and rows, *attributes* to view the qualities of the dataset, and functions such as *sum(is.na x)* that explore missing data. Advanced data cleaning focused on identifying and resolving missing values and detecting and deciding an approach to outliers.

Missing data

Ruben (1976) puts forth a theoretical framework for three categories of missing data. Missing values in one variable unrelated to other measures, and the underlying value of *x*, are considered to be missing completely at random (MCAR), while values possibly related to other measures but unrelated to *x*- are missing at random (MAR) while missing values related to a variable *x* are considered to be missing not at random (Rubin, 1976). If the error is not due to other values, missing data due to malfunctions and glitches is also MCAR. These three instances of missing data are not mutually exclusive and may be present in a dataset. An examination of the study datasets revealed that missing data was completely missing at random, an instance in which the missing data is entirely random with unrelated to other measures in the dataset. The missing data in the study datasets from AAU and UG fall within the first category, CMAR, where the missing value is unrelated to other variables in the dataset. Hence, missing data are distributed randomly without impacting other variables such as gender, region, or level.

Missing variables in AAU datasets are mainly limited to date of birth, with fewer missing values in CGPA. Additionally, the AAU dataset contained negative values and birth dates identifying students as young as one year old. Conversely, the UG dataset was relatively complete, with missing values in CGPA. Interviews during the data collection stage explained the demographic data is self-report at both institutions during the admission process. However, date of birth is a required field for both institutions and must be completed as it is used to determine eligibility for enrollment and placement.[16] The AAU dataset challenge in date of birth may rest with the difference between the European and Ethiopian calendars.[17] Although students

[16] Candidates who are at least 25 years old and can provide proof of age can register for the UG Access course and pass the Mature Student Entrance Examination to gain admission to UG Distance Learning. https://admission.ug.edu.gh/applying/undergraduate/mature-entry/ba-distance-learning

[17] The Ethiopian Calendar is based on the Ethiopian Orthodox Twahedo Church calendar, with 5,500 subtracted from it. It has 13 months, 12 with 30 days each and one with 5 days called Pagumen. Every fourth year, Pagumen has a leap year with six days (Tafesse, 2008).

are directed on month, day, and year format, the eight-year gap between the two calendars may impact users' imputation, resulting in missing dates or negative values in the dataset. On the other hand, grades and CGPA are reported by instructors and deposited in the Registrar database for both AAU and UG. Similarly, the challenge in imputation does not appear to apply to UG missing data, as all missing data were reported as N/A.

Overall, missing data in the dataset was 2% for UG and 16% for AAU. To determine missing data and formulate a plan for handling, the *mice*, *VIM*, and *Hmisc* packages in R were used to investigate the pattern and distribution of missing values. The *md.pattern()* in *mice* package provides a table for detecting the pattern of missing data and indicates missing data in the date of birth columns in both datasets. The *md.pattern()* function on the AAU dataset demonstrates that out of 4,051 objects, 714 had missing values, with 249 missing date of birth and 465 missing CGPA. The *VIM* package produced a visual representation of missing data along with the percentage missing and completeness. The result of running the AAU online dataset indicates 83.4% completion with 6.2% missing date of birth and 11.5 % missing CGPA. Literature on missing data suggests resolving missing data beyond the 5%-10% range with imputation (Ding & Li, 2018; Peugh & Enders, 2004; Rubin, 1976).

Conversely, although the UG dataset was more extensive at 46,092, it was relatively complete, with *md.pattern()* indicating 98% of the values as complete. Missing data was mainly in CGPA 2.4% (1,108), entry year 0.0087% (4), and marital status 0.022% (1). The *VIM* package in R produces an aggregation plot to visualize missing data patterns for the UG dataset.

There are two methods for resolving missing data: imputation or deletion. The deletion method involves listwise deletion, where a unit with missing data is deleted, and pairwise deletion, a more involved statistical method using correlation between two variables (Ding & Li, 2018). Depending on the type of missing data, the deletion method is insufficient for educational research with potential bias, particularly in instances when the missing data is not missing at random and missing at random (Peugh & Enders, 2004). However, MCAR data is less susceptible to these issues and offers a more straightforward approach. In terms of causal inference, the direct approach is to impute missing data and conduct causal inference based on the imputed data (Ding & Li, 2018). Given that the missing data in the study dataset is random, the straightforward approach of imputation is deemed appropriate. Additionally, the imputation method was selected for the study to retain enough online learning units for comparison, particularly in the AAU dataset.

Missing data was resolved using the *Hmisc* package in R by creating imputes based on central tendency measures. *Mean* function is used to impute age (date of birth) and CGPA, *random* for string values, and *median* for marital status. Mean imputation prevents bias in the variable and estimates, while median imputation results in a higher than usual replacement value. Moreover, mean imputation in MCAR is an acceptable approach for missing data.

Outliers

Outliers, observations that are significantly "different (either very small or very large) in relation to the observations in the sample, are potentially problematic in regression, causing issues such as heteroscedasticity (Gujarati, 2003, p. 390). At first glance, there appear to be unusually high and low values in age and CGPA. Graphic representation using *qplot* and *ggplot* packages in R and boxplot implied outliers in the AAU and UG data. Outliers can occur as a natural variation in the dataset, which is the case in the AAU and UG datasets, which includes graduate students who generally returned to school after years in the workplace. While AAU has graduate student enrollment in the middle age range, UG has the mature enrollment option where working adults over 25 returning to obtain a degree.

Moreover, outliers result from an error, such as the challenges observed above in date of birth value in AAU data, contributing to atypical age below the norm for college students. The process of addressing missing data resolved the lower below norm values in the dataset. Although the age of most students falls within the general college age, the values beyond the sample are naturally occurring outliers that occur due to the nature of the graduate and continuing education population and, therefore, are retained in the dataset.

Quantitative data analysis

Although the research on the effect of online learning in the African context is limited, the data points for the study are based on the literature on online learning globally, which has found learning characteristics and demographic profiles as critical predictors of online learning outcomes (Aalangdong, 2022; Alghazo, 2005; Edwin & Yaw, 2016; Faidley, 2018; Nguyen, 2015). Moreover, previous research comparing face-to-face and online learning outcomes highlights limitations on controls for selection bias. Nguyen (2015) points to the difficulty in accounting for endogenous selection bias in online learning, where students with higher learning abilities self-select online learning, thus inflating the effectiveness of online instruction. Additionally, research on the effectiveness of online learning has yielded a wide range of findings and differences across disciplines and other environmental considerations (Aalangdong, 2022; Bernard et al., 2004; Faidley, 2018). Thus, this research utilizes a causal inference framework carried out through a matching process primarily to control selection bias.

Causal effect

This study estimates the causal effect of online learning on the CGPA of participants. The critical distinction between correlation and causality is easy to misinterpret. Correlation denotes a connection between two things, such as the association between exercise and a healthy outcome. Causation shows that a particular action or phenomenon *causes* and *affects* a certain result, such as sun exposure causing sunburn (Goldthorpe, 2001). In statistics, association is inferred through analysis such as regression and hypothesis testing to determine the distribution limits of sample populations to infer probability. However, causal inference is determined by an additional step beyond determining probability to estimating a result of external interventions (Pearl, 2009). Hence, the distinction between association and causation can be understood as "any relationship that can be defined in terms of a joint distribution of observed variables" is an association, while "any relationship that cannot be defined from the distribution alone" is causation (Pearl, 2009, p. 99). Therefore, in statistics, an association can be defined by distribution functions, while the causal effect cannot be defined by a distribution function, necessitating the use of causal inference.

Causal inference

Causal inference determines the independent effect of a treatment (cause), in this case, online learning, on the outcome, GPA. The process considers assumptions, study design, and estimation strategies. The outcome considered includes the potential outcome, the actual observed outcome, the unobserved potential outcome, and the counterfactual (Pearl, 2009). The potential outcome in this study is the CGPA of students in online learning and face-to-face instruction, with the actual observed outcome as a student taking online learning. The unobserved potential outcome is if the student is enrolled face-to-face, and the counterfactual is if those enrolled online are enrolled in face-to-face, which has not occurred and thus cannot be observed.

While it may be challenging to identify the cause of certain outcomes, such as a higher GPA, causation due to exposure to a treatment or intervention, such as online learning, can be established, though not as effectively using regression analysis. Multiple regression analysis is a useful method for correlating data however, it does not consistently and dependably reveal causes. Regression allows the analysis of relationships between one dependent variable and one or several independent variables in the case of multiple regression, leading to the ability to draw an inference or make a prediction of the influence of independent variable(s) on the dependent variable (Gujarati, 2003). However, "the existence of a relationship between variables does not prove causality" (Gujarati, 2003, p. 696). Regression to estimate causal inference poses a challenge because "additional assumptions beyond the data are required to justify the convenient interpretation of multiple regression coefficients as causal effect" (Gelman & Hill, 2006, p. 193).

The process of variable selection for the regression model significantly impacts the analysis of treatment effects. For instance, when a predictor variable is correlated to the error term, when one or more important variables are omitted, and when the outcome variable is also a predictor, it prevents inference of causality (Gelman & Hill, 2006). The challenge lies in accurately interpreting results due to endogeneity, overt bias, and heterogeneity thus, without outside additional information, attributing effect is based on assumptions (Xie, 2011). The issues in using regression in estimating causal inference result in heterogeneous treatment effects, thus preventing the identification of causality, and estimating effect.

The method of identifying causality by statistical inference is known as causal inference. Causal inference determines the actual independent effect of a treatment (cause), in this case, online learning, on an outcome, CGPA. The process considers causal concepts such as randomization, assumptions, influence effects, confounding, and estimation strategies (Pearl, 2009). The outcome considered in causal inference is the potential outcomes, actual observed outcome, counterfactual, and the unobserved potential outcome given intervention (treatment). The challenge in this instance is to determine "whether, or how far, the observed degree of association of variable X with variable Y…can be equated with the degree to which X is causally significant for Y" (Goldthorpe, 2001, p. 2). Hence, although the outcome under observation is associated with the treatment, causal inference analysis determines if the association is the cause of the outcome.

The study uses Rubin's Causal Model (RCM) to determine whether online modality *x* is causally associated with CGPA, *y*. RCM is a framework for causal effect based on observable potential outcomes (Imbens & Rubin, 2015). Rubin defines causal effect with two essential characteristics, first, it is defined by the potential outcome "but is not dependent on which outcome is actually observed" (Imbens & Rubin, 2015, p. 6). Regarding the study, the two treatment levels, whether one is enrolled in online learning or face-to-face instruction, have two potential outcomes, CGPA with online learning and CGPA with no online learning. Hence, the causal effect compares these two potential outcomes and does not depend on which outcome is observed. The second characteristic is "the comparison of potential outcomes, for the same unit, at the same moment in time post-treatment" (Imbens & Rubin, 2015, p. 6). The potential outcome is not defined temporally, such as analysis before taking online or face-to-face instruction and then after, but rather post-treatment after the point treatment has been administered.

The fundamental principle of RCM is "causality is tied to an action (or manipulation, treatment, or intervention), applied to a unit" (Imbens & Rubin, 2015, p. 4). Hence, the unit is simultaneously exposed to two different treatments or actions. However, only one of the treatments has an effect and is, thus, called treatment, while the other is called control. The outcome of the treatment upon the unit is referred to as a potential outcome because it is the action that "will ultimately be realized and therefore possibly observed" (Imbens & Rubin, 2015, p. 4). Therefore, the focus is on observing the potential outcomes of the treated potential outcome, if treatment is applied, and the untreated potential outcome, if treatment is not applied.

The notation for causal inference, *i* denotes the unit under observation, Y_i is the observed outcome Y measured in unit i. T_i indicates the actual observed treatment condition for unit i, T_i is the actual observed treatment condition for unit i and $T_i = 1$ signifies the units/subjects assigned to the treatment group while $T_i = 0$ are unit/subject assigned to the control group. Treatment groups are $Y_i(1)$ and the actual observed outcome of treatment= $Y_i(1)$ | $T_i = 1$. Control assignments are $Y_i(0)$ and actual observed untreated potential outcome = $Y_i(0)$ | $T_i = 0$. The two potential outcomes are $Y_i(1)$ for the treated potential outcome is the outcome for unit i if it had received the treatment and $Y_i(0)$ for the untreated potential outcome is the outcome for unit i if it had not received the treatment Table 2 identifies the notation for this study.

Table 2: Study Notation

Notation	**Definition**	**Addis Ababa University**	**University of Ghana**
Y	Observed outcome	CGPA	CGPA
i	Unit of measure	Enrolled students	Enrolled students
Y_i	Observed outcome Y (CGPA) measured for unit i (students)	CGPA of 1,015	CGPA of 11,174
T_i	Treatment group	1,015	11,174
$T_i = 1$	Students enrolled in online learning	1,015	11,174
$T_i = 0$	Students enrolled in face-to-face instruction	3,036	34,918

In causal effect, Y_i is assigned a value of 1 or 0 where the value of T determines the observed outcome. If assigned treatment group, $T_i = 1$, then the observed outcome is the treated potential outcome, Y_i= $Y_i(1)$. If assigned control group, $T_i = 0$, then the observed outcome is the untreated potential outcome, Y_i = $Y_i(0)$. Therefore, $Y_i(1)$, $T_i = 1$ denoting that the treated potential outcome for a unit i given that unit i received treatment and $Y_i(0)$, $Ti = 0$ signifies that the untreated potential outcome is the outcome for unit i if that unit i had not received treatment. Hence, the potential and observed outcome of Y_i is Y_i = $T_i(1)$ + (1-T_i) * $Y_i(0)$.

Another element of RCM, the counterfactual outcome, is the “value of the potential outcome corresponding to the treatment not applied” (Imbens & Rubin, 2015, p. 5). This concept captures the never observed instances and cannot be observed because they did not occur. Estimating the effect of an intervention is carried out through the observed outcome, “observed realizations of potential outcomes, and because there is only one realized potential outcome per unit” (Imbens & Rubin, 2015, p. 7). The counterfactual potential outcome is the outcome we do not observe since it did not take place. For instance, in a treated group, the counterfactual potential outcome is untreated, and in the control group the counterfactual potential outcome is the treatment. For those assigned to control, unobserved untreated potential outcome notation is $Y_i(1)$ | $T_i = 0$ while those assigned to treatment, unobserved untreated potential outcome = $Y_i(0)$ | $T_i = 1$.

The counterfactual asks what the effect would be on the treated if they had not received treatment or on those who did not receive treatment if they had received treatment. However, since this phenomenon does not, and cannot, occur, it is unobservable (Imbens & Rubin, 2015). The study cannot observe the counterfactual effect of face-to-face instruction on those enrolled in online learning and the effect of online learning on those enrolled in face-to-face instruction, as these phenomena are unobservable. Therefore, the focus of analysis is those enrolled in online learning and those not enrolled in online learning, i.e., face-to-face instruction, as these are the potential outcomes of the treatment of online learning. The counterfactual, the potential outcome of those enrolled in online learning if they were not enrolled in online learning, does not take place, and hence cannot be observed.

Types of treatment effects

There are several treatment effects in causal inference, which are carried out in the study to estimate effect at various levels, including effect among the treated and within a population, however, the individual effect cannot be estimated.

Unit causal effect

The unit causal effect of a treatment on the individual *i* is the difference between treatment and control, holding all other variables equal. This is called the unit treatment effect, which compares the treated and untreated potential outcome at the individual level.

$$UTE_i = Y_i(1) - Y_i(0)$$

The unit causal effect is sensitive to the interaction effect, where variables may interact with treatment to alter the treatment effect. The interaction effect leads to heterogeneity in causal effect due to differences between individuals or due to the impact of interaction effects on an individual. This means that two people will have different causal effects, and the same person may have a causal effect depending on the variable.

Average Treatment Effect

The primary estimate for the study is the Average Treatment Effect (ATE), which estimates the average treatment effect on the entire population, both treatment (T_i = 1) and control group (T_i =0). ATE measures mean (average) outcomes between the treatment and control groups. In this instance, the UTE for each individual is calculated and then averaged to determine the ATE for the entire population.

$$ATE = sum\big(Y_i(1) - Y_I(0)\big)/n.$$

In observation of i across $Y_i(1)$, treatment group, and $Y_i(0)$, control group, the average of the value of $(Y_i(1) - Y_I(0))$ across the entire sample yields the ATE.

The disadvantage of ATE is that it is difficult to witness both the treated and untreated potential outcomes for each individual, making it difficult to determine the counterfactual (unobserved potential outcome) for each person. Hence, for each individual, either $Y_i(1)$ *or* $Y_i(0)$ is known, but not both. Additionally, ATE does not estimate the benefit/harm of treatment on an individual but provides a distributed effect of treatment across the sample. And finally, ATE is more suited for randomized experiments than for observational studies where there is an element of self-selection. Without controlling self-selection, it leads to biased estimates.

Average Treatment Effect on Treated

The study also provides estimates for the Average Treatment Effect on Treated (ATET), which measures the effect of the treatment on those who receive the treatment. The average UTE for the people that have been treated is calculated and then averaged.

$$ATET = sum(Y_i(1)|T = 1) - (Y_i(0)|T = 1)/n.$$

Assumptions

There are several assumptions in matching, which will be observed in the study. In casual effect, assumptions are not “informed by observation” but are instead “acquired knowledge of the subject matter” (Imbens & Rubin, 2015, p. 10). For randomization in observational studies where the outcome is independent of treatment but conditional on *x*, all variables relevant to the probability of receiving treatment are observed and included in *x*. However, a few conditions/ assumptions must be satisfied for accurate causal inference.

Stable Unit Treatment Value

The Stable Unit Treatment Value (SUTV) assumption was the primary consideration in limiting the comparison of online learning and face-to-face instruction within an institution. Since there are significant differences in the administration, management, and deployment of online learning between AAU and UG, comparing results across intuitions would have required comparing results at two vastly different treatment levels, yielding inaccurate estimates.

The primary assumption is the SUTV which postulates the stable unit treatment value assumption is critical for causal inference as it assumes the consistency of the treatment group and non-inference with the treatment administered (Caliendo & Kopeinig, 2005). The stability of treatment value assumes the uniformity of treatment across units, which is key to comparison and estimating effect. SUTV assumes "[th]e potential outcomes for any unit do not vary with the treatments assigned to other units, and, for each unit, there are no different forms or versions of each treatment level, which lead to different potential outcomes" (Imbens & Rubin, 2015, p. 10). This assumption states there is no variation in treatment, such as one unit is exposed to the treatment of higher efficacy while others are exposed to a placebo or lower efficacy treatment. Moreover, the potential outcome of any unit does not pose an impediment or obstacle to the potential outcome of other units. Hence, the potential outcome of each individual in online learning enrolled in a course/ program does not interfere with the potential outcome of others.

Assumptions for variable selection

The selection of variables for the study aligned with the Conditional independence assumption (CIA) and common support assumption. Numerous variables were present in the datasets from AAU and UG, but only those that explain rather than affect the outcome and are common to all institutions were chosen for analysis. However, as previously stated, due to data collection and management practices in the study sites, the study lacks all the variables that may affect treatment and outcome.

CIA stipulates an observable variable (x), where potential outcomes are independent of treatment $(Y_1), (Y_0) \perp T_i|X_i$ (Caliendo & Kopeinig, 2005). This means the assignment to the treatment group is independent of covariates/ characteristics. Conditions under CIA include ignorability, where the difference between treatment and control groups can only be ascribed to treatment, and selection bias, where a variable affects either the treatment or control group.

CIA is also known as confoundedness. A confounder is a variable with direct or inverse causal relationships to the dependent and independent variables (Imbens & Rubin, 2015). Confounders in observational studies indicate there is more than one cause for a particular outcome. Hence, confoundedness in observational studies impacts variable selection; variables that affect treatment without effecting outcome should not be included. As the goal is to ensure that outcome is independent, variable selection should be based on impact treatment and outcome, and variables that impact outcome but not treatment may be included.

Common support assumption $0 < P(T = 1|X) < 1$ where treatment for each characteristic x is as likely of the probability of not receiving treatment (Caliendo & Kopeinig, 2005). The assumption stipulates there should be many commonalities in the characteristics of treated and untreated for adequate matches. This is essential since the matching process requires a larger control group than the treatment group to ensure all treatment units are matched and the treatment group is matched with the best/closest match.

Matching

The study estimates the causal effect online learning on CGPA takes place through matching. Matching is defined as "any method that aims to equate (or "balance") the distribution of covariates in the treated and control group" (Stuart, 2010, p. 1). Matching offers a method of estimating causal inference in observational data with reasonable closeness to randomized experiments. In instances where randomized observation is not possible, such as nonexperimental research with secondary data, a non-random assignment system is required to determine the causal effect (Imbens & Rubin, 2015). Although random assignment experiences provide greater accuracy and efficiency, when such experiments are not possible, the matching method is essential for nonexperimental studies for randomization and to minimize selection bias in estimating treatment effect.

Although matching can be used in observational studies to infer causality, it lacks the precision and clarity of random assignment experiments. Matching is less accurate and efficient at estimating treatment effects than random assignments because it cannot fully account for selection bias. The matching process can account for observable covariate selection bias but not for unobservable confounders or variables not included as matching criteria. These omissions could include unobserved differences between the treated and control groups, resulting in selection bias and potentially affecting the validity of the estimated treatment effects. In random experiments, both observed and unobserved confounders are detectable. The ability to equal distribution across treatment and control groups increases the likelihood that all differences can be attributed to treatment.

The availability of covariates in the research data set may influence the matching process by limiting control matches for treated units, where matched pairs may not represent the population, affecting generalizability. Random assignment findings, on the other hand, are less dependent on individual characteristics, allowing for more substantial external validity and greater generalization. Finally, random assignment improves the accuracy with which causal effect is estimated. The procedure provides for the formation of treatment and control groups at random, reducing the possibility of selection bias and avoiding structured differences between groups.

Instead of random assignment, the matching process balances the distribution of covariates between control and treated groups through a process of sub-setting a database with the goal of balancing covariates in treated and control groups to ensure the characteristics of the two groups match except for the treatment (Stuart, 2010). Participants in the treatment differ from those who did not participate, thus creating a selection bias. In online learning enrollment, selection bias is a significant factor, as noted earlier by Nguyen (2015), with the potential to overstate online learning effectiveness. This endogenous selection bias “is the key consequence of the absence of randomization” (Rosenbaum, 2010, p. 354). Matching minimizes selection bias through covariate balancing before and after matching, and model-based adjustments assist in detecting bias (Stuart, 2010). Additionally, ensuring characteristics are shared across treatment and control groups and data with a wide selection of nonparticipants with similar characteristics minimizes overt bias. The study data meets this criterion with 34,918 face-to-face and 11,174 online for UG and 3,036 face-to-face, and 1,015 online for AAU, providing a bigger pool of nonparticipants available for matching.

The study lacked all variables that potentially affect treatment and outcome. Several factors influence the number of covariates required for propensity score matching. Matching aims to create comparable treatment and control groups by matching units with similar estimated probabilities of receiving the treatment based on their propensity scores. Covariate matching reduces selection bias and results in more balanced comparison groups. There is, however, no minimum or maximum number of covariates required. Considerations in variable selection include variable relevance, support in achieving balance and avoiding overfitting the model with a large set of variables (Vuolo et al., 2018).

Covariate selection in matching is focused on satisfying the conditional independent assumption (CIA) and the relevance of covariate in determining treatment and outcome (Caliendo & Kopeinig, 2005). Since this study is investigating the effectiveness of online learning, the variables chosen focused on demographics and digital access, both of which have been shown in previous studies to be important in determining enrollment in the modality and outcome. Furthermore, the study covariates aid in achieving balance since covariate distributions were similar across groups, reducing the bias introduced by confounding factors. Finally, including too many variables increases the risk of overfitting, which occurs when the model becomes overly complex and unfit for generalization, resulting in discarded treated units and multiple matches to control units.

Therefore, covariate selection and number are more focused on model design and theory, hence “a sound knowledge of previous research and also information about the institutional settings should guide the researcher in building up the model” (Caliendo & Kopeinig, 2005, p. 5). This study followed the general guideline to include sufficient covariates to balance observable characteristics between the treated and control groups. The study’s variable selection was based on literature and research in the field and the context of the study institutions, as discussed earlier. A larger dataset, on the other hand, would have allowed for the development of subset variables for a more robust model. The UG dataset contained six covariates, while the AAU analysis consisted of five, with all variables shared by the treated and control groups.

The advantage of the matching process lies in the ability to detect and check overlapping covariate distribution from which a more accurate effect can be assessed (Stuart, 2010, p. 2).

According to Stuart (2010), the goal of achieving balance is critical in the matching process consisting of defining the closeness of a match, matching based on distance, and the iterative process of assessing the quality of the matches, which leads to estimation effect with close proximation to randomized research. Methods such as regression and selection, which do not have this attention to covariate balance, have demonstrated low functionality in detecting and checking for such covariate overlap (Gujarati, 2003). Moreover, linear regression has been shown to increase bias in cases with a nonlinear relationship between outcome and covariates (Stuart, 2010).

This study utilized matching rather than Ordinary Least Squares (OLS) to perform causal inference analysis. OLS is a regression analysis method that estimates the relationships between independent variables and a dependent variable to find the best-fit line that reduces the sum of squared residuals. The sum of squared residuals (SSR) can explain variability in the dependent variable by measuring the difference between observed and predicted values in the model. Although OLS regression does not detect causal relationships, it can be used to estimate the average effect of the independent variable on the dependent variable (Gelman & Hill, 2006). A matching method, such as propensity score, on the other hand, can estimate effect by creating a treatment and control group from which effect can be estimated among comparable units in terms of observed variables (Brazauskas, 2016; Rosenbaum, 2010; Vuolo et al., 2018). Matching necessitates a larger dataset as it has the potential to be less effective if there are not enough control units that match treated units and observations are discarded. The study data contains a higher proportion of control units than treated units, with the UG dataset containing 75.76% control units and the AAU dataset comprising 74.94%. Hence, the sample size is essential for ensuring matches for treated controls, therefore, the number of observations required for successful matching will depend on the availability of control units. However, for statistically significant results, a larger sample size is needed.

As previously stated, obvert bias is an issue in causal inference. One limitation of OLS in causal inference analysis is that it would not directly address treatment and selection bias since the assumption is treatment assignment is random and fails to account for potential biases caused by non-random treatment assignment (Gelman & Hill, 2006). Overt bias may exist due to observed variables between the control and treatment groups, such as age, gender, and marital status. That is, the profile of those enrolled in online learning courses may differ from those enrolled in face-to-face instruction. However, observable confounders must be controlled to determine the treatment effect and ensure that the difference in outcome can be attributed to treatment and not another factor (Imbens & Rubin, 2015; Rosenbaum, 2010). To reduce bias caused by non-random treatment assignment, matching addresses treatment assignment by creating comparable groups of treated and control units and balancing observed covariates across groups. Therefore, matching can investigate treatment effect within a specific profile rather than across the sample, where observed variables may influence the outcome. To determine the treatment effect of online learning, for example, students with similar profiles, such as male, 24 years old, and single, are grouped for comparison to eliminate the effect of gender, age, and marital status.

Furthermore, OLS is particularly vulnerable to outliners, which are observations that deviate from other observations (Rousseeuw & Leroy, 2003). Outliers are not always the result of errors in data collection and entry and can also occur naturally due to the natural variation in the data, as in the case of UG and AAU data. For example, Students older than the traditional undergraduate and graduate age groups can enroll in both institutions' programs and admissions processes. It may appear as an outlier in OLS analysis, affecting parameter estimates and model fit. Outliers in OLS can significantly impact the coefficients by giving more weight to data points with higher residuals, which leverages the regression line and distorts coefficient estimates (Rousseeuw & Leroy, 2003). OLS regression did not appear suitable given the nature of the study datasets; however, comparing units with similar and relevant variables across treatment and control groups reduces the impact of confounding variables and manages the outsized effect of outliers.

Propensity score matching

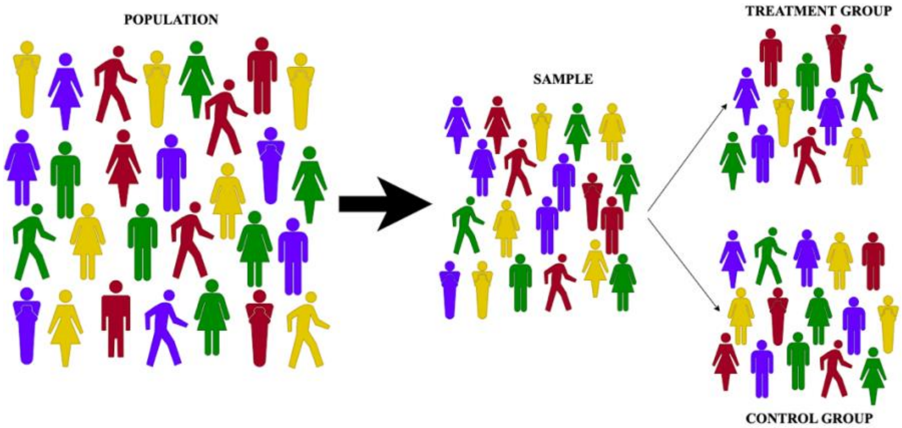
Rosenbaum & Rubin (1983) observed in nonrandomized experiments, a direct comparison of two treatment groups has the potential to yield inaccurate results since units across both treatment groups differ. They proposed a method where "balancing score *b(x)*...as a function of the observed covariates *x* such that the conditional distribution of x given *b(x)* is the same" for treatment and control groups. One such balancing score is the propensity score, "the conditional probability of assignment to a particular treatment given a vector of observed covariates" (Rosenbaum & Rubin, n.d., p. 41). Thus, the propensity score is the conditional probability that an individual in the full sample received treatment given a set of observed variables.

Propensity score matching is the matching process based on the propensity score. According to Rosenbaum & Rubin (1983), the propensity score model $e(x_i)$ is the conditional predicted probability of being assigned to a treatment group $(z_i = 1)$ or a control group $(z_i = 0)$, given observed covariates (x_i)

$$e(x_i), = Pr\ (z_i = 1 \mid x_i)$$

A propensity score matching is a number that summarizes all the units' covariates by first generating the propensity score number for all units, which is then compared to find units with the same propensity score values. The propensity score matches produce valid matches for estimating the impact of the treatment based on the propensity score rather than the value of variables, which, as discussed above, pose significant challenges in determining causality.

Figure 6: *Propensity Score Matching*



If a treated and control unit have the same propensity score, then any observed difference between the two has been automatically controlled through the procedure variables (Li, 2012). In propensity score matching, the observations are placed into two groups, the group that received the treatment, known as treat, assigned 1, and the group that did not receive the treatment, known as control, assigned 0. The propensity score is calculated using the *logit* or *probit* model, followed by matching treated and untreated units on the propensity score to estimate the treatment effect and calculate standard errors.

Matching in r

Matching in *r* was done using *MatchIt*, a program for improving models before performing logistic regression analysis using the *glm()* function, and *Match*, a program that evaluates model fit using logistic regression (*glm())* function and then performs matching using the fitted model *(see Table 3).* The next chapter provides a detailed discussion of outcomes and comparisons of the two methods. The matching analysis starts with matching, then uses several approaches to assess the quality of the matches, and lastly, estimates the treatment effect.

Table 3: *Procedure for matching using* MatchIt()
Conduct a match based on PS, trying different matching methods to determine the appropriate method.
Build a *logistic* regression model using *glm()* to predict treatment and variable to generate a probability of receiving treatment (i.e., enrolling in online learning)
Check the balance of covariates between treatment and control groups by calculating the balance through statistics and plots.

The complete dataset is used for UG matching, followed by undergraduates and students retaking the course. Matching is done across the board as all online programs for the AAU data are graduate level. Treatment is designated as “treat,” with campus-based treatment assigned 0 and online treatment assigned 1. Age, gender, marital status, level, and CGPA are covariates for UG, whereas CGPA, year, gender, and age are covariates for AAU (level). The first matching method was the nearest neighbor, a “procedure [that] matches participants from the control group to participants from the treatment group based on closeness” (Olmos & Govindasamy, 2015, p. 73). The distance measure supplied by the distance option logit in both functions. Each treated unit receives a match, chosen in the order specified by the *m.order* command, with the default being from largest to smallest. The control unit, not yet paired but closest to the treatment unit, is chosen based on the distance measured at each matching step. The nearest neighbor can be understood as a control unit treatment participant P_j is a match for a treated unit $P_{i,}$ If the absolute distance between their propensity score, P, is the smallest $C(P_{i)} = min_j \| P_i - P_j \|$, j ∈ I_o. The nearest neighbor matching method requires a pool of more control units than those in the treatment. The AAU dataset has 3,036 control and 1,015 treated units, whereas the UG dataset contains 34,918 control and 11,174 treatment units. Therefore, the size of the control units in each data set provides ample opportunity to identify the best control matches for all treated units. However, the nearest neighbor method did not produce an adequate balance.

A second attempt using subclassification method “of controlling for systematic differences involves grouping units into subclasses based on observed characteristics, and then directly comparing only treated and control units who fall in the same sub-class” (Rosenbaum & Rubin, 1984, p. 516). The subclassification method is straightforward and is optimal for reducing bias compared to other more complicated methods due to its focus on matching based on the propensity score. In instances of significant skew data, as in the study’s dataset, using a subclass of 5 strata ($k=5$) reduced bias by 94%. The study used a subclass of 6 strata (k=6) based on propensity score to achieve a balance of covariates.

The matching results are studied using statistical approaches and visuals such as graphs and plots. The summary of matching was demonstrated visually through *plot()* function and statically in the output of the match. *Plot()* was also used to illustrate balance through graphing before and after matching and the distribution of propensity scores. The package *love.plot()* was used to generate visual graphs showing the balance of covariates after matching. A complete set of matching and balance checking statistics and visuals can be found in Appendix VI

Limitations

The study’s main limitation rests with the fragmentation and irregularity of data from the study sites. PSM requires that the model includes all covariates that potentially explain variation in the potential treatment effect. However, the study was able to collect a range of covariates such as age, gender, marital status, program, unit, and level as these were the only relevant data points available from the institutions. However, while these covariates are important in selecting treatment, it does not constitute all the covariates for determining treatment. As there are more control units than treatment units, the treatment group is sufficiently represented in the sample data, increasing the likelihood that all treatment units will be matched. Finally, applying the subclassification approach in matching, which lowers bias and improves generalization, helps to mitigate the study's limited variables (Tipton, 2013).

The nature of data collection in the study institution has implications for the range of courses included where the study does not include all courses, whether campus-based or online. The extent to which relational data approaches are used across the several data gathering locations in AAU and UG is unknown. AAU is organized across fifteen campuses in and around Addis Ababa. For instance, *Sidist Kilo* is the main campus and houses primarily social science and huminites colleges and institutes, *Arat Kilo* campus house the physical and natural science, however, medical-related training is spread across *Tikur Anbessa*, *Bishoftu* Campus, and *Amist Kilo* Campus.[18] Each campus has some level of autonomy within specific functions. Some campuses obtain services from the main campus for data gathering and online learning, while others perform these tasks themselves. Consequently, only the courses the AAU Registrar's Office can access are included in the study dataset obtained from AAU.

On the other hand, although UG is contained within one campus, similar arrangements exist in terms of functions such as data gathering and online instruction. UG Computing Services is the primary hub for all data collected across the institution, however, access to the complete dataset is limited. As the study dataset was accessed through the Institutional Research Office, the parameters for downloading requested data did not include professional schools such as law and medicine and online courses delivered through departments.

[18] Organization of Addis Ababa University campus and colleges can be found at http://www.aau.edu.et/about/aau-campuses/

Qualitative

This study's explanatory mixed method design leverages the qualitative multiple case study method to explore quantitative findings in more depth. In the quantitative phase, this investigation focuses on the statistical comparison of face-to-face instruction and online learning, with CGPA as the outcome. The qualitative phase of the multiple case study asks how the deployment of online learning in AAU and UG has contributed to the effectiveness of online learning in the respective institutions. Although quantitative results offer a numerical data process to determine the efficacy of online learning, the qualitative phase is essential to explore in-depth the modality within the context of each institution to consider the results from the statistical analysis (Yin, 2009). Hence, this multiple case study explores the evolution, administration, and process of integrating technology and user experience in two distinct cases to contextualize quantitative findings.

Qualitative case study

The study design is a comparative case study carried out in AAU and UG independently, comprising an iterative process of theory identification, case selection, data gathering, and comparative analysis within and between cases (Flick, 2007). A comparative case study approach involves a two-stage inquiry consisting of identifying "specific units of analysis and compare and contrast." In this study, we followed AAU and UG using a "processual logic [that] traces across individuals, groups, sites, and time periods" for context, space, and place to reveal linkages and trace processes that contextualize findings from statistical analysis (Bartlett & Vavrus, 2017, p. 8). With this approach, it is possible to compare processes across institutions and perform multilevel, individual, and organizational contextualized analysis of each institution's deployment of online learning.

Qualitative data sample

Participants for the qualitative portion were selected based on proximity to the deployment of online learning within their respective institutions. AAU and UG Interviews focused on individuals with primary responsibility in the deployment of online learning, including lectures, technical personnel, and students. Additional interviews were conducted with external tech experts, including the technical lead of an undersea cable development project and local IT professionals, to understand local ICT infrastructure and best practices in connectivity and networking. Focus groups consisted of students and lecturers, and in the case of UG staff and leadership of both urban and rural learning centers, to better understand the role of learning centers. The document analysis included online and printed documents, in the same way, observations consisted of virtual and in-person. Documents included online curriculum, quality assurance documents, and implementation notices and instructions for students. There was an opportunity to observe a demonstration of the UG online learning platform and an online course. These methods provided comprehensive knowledge on the operationalization of online learning in AAU and UG, which was leveraged to place the quantitative findings in context.

Ravtich and Carl (2016) recommend selecting a site related to research goals, this should be an active part of the discussion to support processing the topic. All in-person interviews took place on campus and, for participants with designated offices, in their spaces to ensure comfort. However, due to COVID-19 closures, earlier interviews and focus groups were conducted virtually, while those undertaken after lifting restrictions took place in person. However, due to prolonged unrest in Ethiopia, AAU interviews were conducted via Zoom.

Qualitative study instruments

The case study instruments included in-depth interviews, focus groups, observations, and document analysis. The semi-structured open-ended interview questions begin with the participant's technological experience and personal assessment of their digital skills, then proceed to previous experience with online learning and their views of the institutions' technological readiness and online platform. The interview delved deeper into the participants' experiences with online learning for a broad institution-based understanding. Focus group open-ended questions were designed to elicit discussion on participants' knowledge, experience, and perspective of the institution's online learning program, focusing on the strengths and shortcomings.

The document analysis offered background and context of official policy and operational guidelines of modality, which was compared with data from interviews and focus groups for a comprehensive analysis of conditions and context of online learning in respective institutions (Hammarberg et al., 2016), Document collection in the form of program information and notices, course syllabi, etc., to understand the program design and its implementation. This collection and analysis will reveal the "ideas and assumptions, and…knowledge and opinions" on the program. (Norum, 2012, p. 27).

Observation, as a tool, "explores and describes the mediating contexts on behavior, attitudes, beliefs, and interactions" (Ravitch & Carl, 2016, p. 160). There were multiple opportunities to observe the leadership, staff, and cohort members in their settings for insights into policy and practice alignment. Descriptive field notes were a component of the observation as annotation exclusive of inference, evaluation, or interpretation (Ravitch & Carl, 2016, p. 162).

Qualitative data analysis

The qualitative analysis used a non-valuative method for interviews and focus groups to "understand what [interview] participants think, feel, and experience" about online learning (Ravitch & Carl, 2016, p. 148). The data analysis used interviews and other gathered data to illustrate and sketch the narrative of online learning in each respective campus. The context of technology deployment, experience in operating systems, leadership perspective, and decision-making within the context of each case is essential to build a sense of which elements promote success in online learning and where challenges may exist.

Data analysis was ongoing throughout the collection process. Throughout the collection process, the completeness and exactness of the data collected was confirmed and verified to preserve the accuracy of the information. Transcribed interviews were coded, and participants were provided with a transcript and, in some cases, asked for clarification and additional information (Ravitch & Carl, 2016). Analytical memos were developed using transcribed interviews and field notes linking relationships and categories of data.

Case study data was coded and analyzed using deductive coding, which allows for drawing on the constructs and concepts identified in the literature and quantitative findings (Ravitch & Carl, 2016). Two cycle coding was used to classify and analyze data using keywords linked to quantitative results. A list of initial codes was developed based on the study's earlier research questions and code definitions. The first cycle of coding consisted of structural coding to organize interviews and focus groups data related to the research questions and quantitative findings. In addition to categorizing, "connecting strategies" were employed to "create the context of the data," where the emphasis was on what connects rather than what separates AAU and UG data (Ravitch & Carl, 2016, p. 252). The second cycle focused on thematic coding to find reoccurring patterns and concepts linked to the key propositions of the quantitative. Ultimately, the final data analysis yields assertions that can be matched and paired with empirical quantitative data (Yin, 2009). Analytical memos and vignettes were written in each case to synthesize the data.

Descriptive validity was used for validation, in which information, facts, and the situation are reported as seen and heard without elaboration. This process is akin to the “concept of reporting and primary understanding” (Maxwell (1992) in (Hayashi et al., 2019, p. 100)). We relied on Runciman’s (1983) concept of reporting and primary understanding and the interdependence of observations and descriptions with the theory used in the research (Runciman (1983) (Hayashi et al., 2019, p. 100)). This process allowed documentation of interviews and observations without external input and assumptions. In areas where ambiguity and vagueness exist, participants were asked to expand and clarify instead of drawing conclusions.

Theoretical validity was used to determine to what extent the theory was consistent with the data. This process checked “the validity of the blocks (concepts, categories)…and the ways that the blocks interact and relate when they are put together” (Hayashi et al., 2019, p. 100). Theory is composed of two parts the concepts and categories, and a part that explains how the concepts and categories are related.

Summary

This chapter discussed the research context and central questions in investigating online learning in Ghana and Ethiopia. The selection of UG and AAU as two examples of online learning to highlight the varied contexts in Africa served to increase the study’s generalizability. The process of selecting institutions included assessing the diversity of circumstances and connectivity at the institutional and national levels to enable applicability to different contexts on the continent. Moreover, the availability of established online learning programs with sufficient student enrollment was a consideration in the selection of study sites.

A mixed-method research methodology was adopted to statistically examine the efficiency of online learning, which was contextualized by a qualitative comparative case study. Discussion of the choice of methods and their suitability for this investigation was documented by the literature and a demonstration of its fit to the study. The quantitative study is a randomized non-experiment employing a causal inference analysis based on Rubin's Causal Model and the principle that cause is linked to action. A discussion of causal inference includes study notation and the matching process. Propensity Score Matching was selected for causal inference analysis, and the difference between PSM and OLS in randomized experiments is reviewed in this chapter.

The qualitative study was a dual case study, which sought to provide context for understanding the deployment of online learning in UG and AAU. Online learning is both an academic and digital process and the interaction of these elements within each institution is essential to understanding the qualitative results. The qualitative methods included interviews, focus groups, document analysis, and observations. Due to COVID-19, interviews were conducted at different points in the research, and while some were in person, others were carried out on Zoom. The qualitative analysis included two-cycle coding, first level structural followed by thematic coding, and descriptive and theoretical validation to ensure an unbiased approach and alignment with the theoretical basis of the study.

CHAPTER 5 | Quantitative Analysis

Introduction

This chapter presents the quantitative findings of the sequential mixed-method study on online learning in UG and AAU. The quantitative analysis was completed first to allow the results to inform the qualitative research. The study used causal inference for quantitative analysis using PSM with the objective of comparing learning outcomes as measured by CGPA based on characteristics to determine the causal effect of online learning, the treatment, as opposed to face-to-face instruction. The outcome was CGPA, and the variables were age, gender, marital status, level/year, semester, program, and unit.

The difficulties in acquiring empirical data for analysis may partially account for the absence of literature comparing online learning and face-to-face instruction in African HEIs. However, the study collected adequate data to compare online learning at the undergraduate and graduate levels in two flagship African universities, the University of Ghana (UG) and Addis Ababa University (AAU). Institutions are treated independently in the ensuing discussion, with descriptive data and PSM findings discussed separately for each institution. This arrangement highlights the decision to analyze each institution independently to reinforce the difference in approach in deployment methods between UG and AAU and comply with the similar treatment condition described in the methods chapter.

The quantitative research question was, “Is online instruction as effective as face-to-face instruction as measured by learning outcomes?” The causal inference method with propensity score matching was employed to assess whether there was a relationship between modality and CGPA.

Quantitative findings

The quantitative component aimed to compare the efficacy of online learning to face-to-face instruction by answering the first research question, "Is online instruction as effective as face-to-face instruction in terms of learning outcomes?" Using a causal effect analysis, the quantitative study investigated whether there was a causal relationship between the modality of instruction and CGPA. Secondary data from UG and AAU of students enrolled in both modalities, online and face-to-face, during the academic year 2018-2019 comprised the quantitative dataset. Since the modality deployment at UG and AAU differed, they were analyzed separately in the causal effect analysis and throughout the quantitative study. The UG's online learning is mainly at the undergraduate level, serving as a vehicle for expanding access to impacted/over-subscribed courses. It is also a pathway for adult learners to return for certification. For this study, the focus was on the undergraduate level. AAU's online learning was available at the graduate level at the time of data collection and developed and offered at the department level. The quantitative instruments are in Appendix VI, which consists of Markdown documentation of the process, codes used to conduct descriptive statistics and PSM, and technical notes.

Descriptive statistics

Descriptive statistics were used to analyze aspects of the data set and to summarize, interpret, and compare selected variables to investigate further the quantitative research question (Lee, 2020). Furthermore, before proceeding with causal inference analysis, it was essential to consider and explore the demographic profile of the entire student body, particularly online students.

University of Ghana – Study Variables

The UG dataset was composed of undergraduate students, and the age structure demonstrates a high representation of younger students. On the other hand, the AAU dataset was graduate students, as that was the only level where online learning was available. The data set and student characteristics highlight the unique features of each institution. UG had a broader reach in terms of student demographics and regional outreach and reflected Ghana's high Gender Parity Index GPI score in educational access. AAU is transitioning from an undergraduate and graduate level institution to a research and graduate training institution. These characteristics are consistent with the founding principles of the institutions, where UG was mandated with expanding educational access, and AAU was established to undertake workforce development for state and governing institutions.

The UG and AAU data set structure illustrates the importance of matching in causal effect analysis. Initially, the data sets indicate variance between face-to-face and online learning in several study variables. A closer examination of frequency and variance supports the premise of less variance within modality and greater differences between modalities. However, upon closer inspection, online learning enrollment accounts for slightly more than 25% of enrollments. The low representation has the effect of drowning out the characteristics of the online learning students, which appears to have been obscured by the over-representation of face-to-face instruction enrollment. When matching is used, however, and learning outcome comparison is based on characteristics, the results reveal a different story, which will be discussed further in this chapter.

The data set from the University of Ghana included students enrolled in online learning programs as well as those enrolled in face-to-face instruction of the online version of the courses and within the units offering the online programs. The study data set is explored in three layers, all students (the full data set), face-to-face instruction only, and online learning only, to compare online and face-to-face instruction as well as survey group characteristics. Appendix VI contains a more detailed examination of all variables.

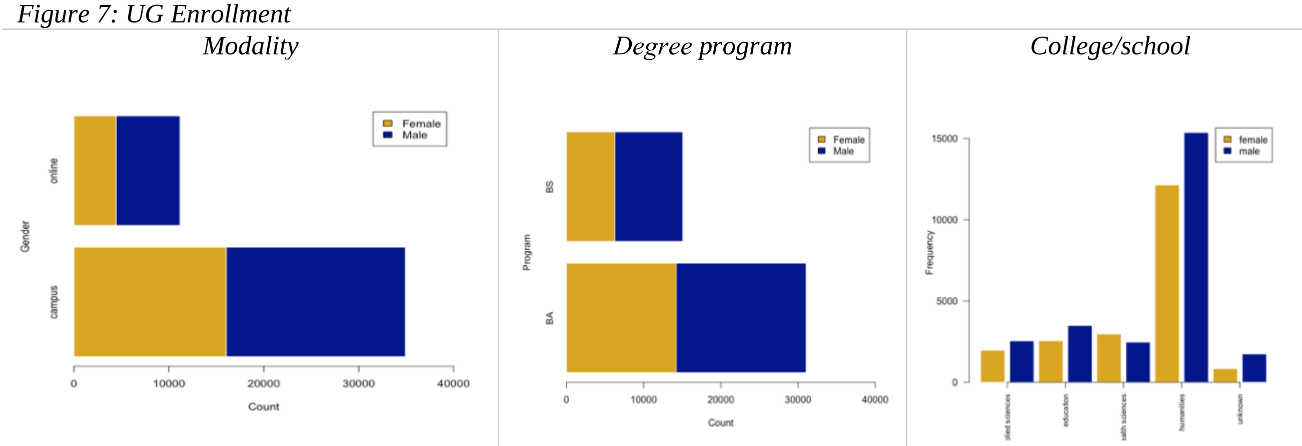
The data set reflects the variety of avenues used to create online courses at UG. Online learning is commonly used to relieve overcrowding caused by limited campus capacity for specific programs, hence, enrollment data primarily contains undergraduates. Applicants with GPAs below a certain threshold who apply to oversubscribed programs are assigned to the online version, while others choose the online version due to convenience and accessibility. With the increased demand for admission as a result of the free Senior High School (SHS) policy, more programs are now offering online versions to accommodate qualified applicants. Aside from these courses, the DDE develops its own online-only courses, including a few graduate level programs. All online courses are available through the UG learning centers in Accra and throughout the country.

Cumulative GPA is the outcome for the investigation. The mean CGPA for all students enrolled was 2.5, and the median was 2.6. For those enrolled in online learning, the mean was 2.3, and the median was 2.31, while for face-to-face, it was 2.6 and the median was 2.7 *(see Figure 9)*. The data set indicates face-to-face students have higher learning outcomes than online learning students. This is borne out in examining the frequency distribution of CGPA on a 4.0 scale for all enrolled students was asymmetrical, with a high distribution of data, higher CPGA, to the right tail and a long tail on the left, for a left-skewed distribution of -0.48, indicating the presence of more values in the higher range of the GPA scale. Similarly, the IQR for CGPA in the same group is 1, which is the difference between 2 and 3, revealing that 50% of CGPA scores are within this range, with a small percentage less than 2 and greater than 3.

However, the dataset contains a large number of dropped classes/dropouts. Of all students enrolled, 1,108 students did not complete the program. When the drops were disaggregated by modality, 1,055 were from face-to-face enrollment, while only 53 were from online learning (95% of the drops in the data set are attributed to face-to-face instruction). In the full data set, 521 drops were female and 587 were male, whereas 20 were male and 33 were female for online learning. Face-to-face students appear to have a higher rate of incomplete and dropout, and male students make up a slight majority.

Although UG does not keep track of dropouts or incomplete cases, there are several possible reasons why face-to-face courses have a higher drop rate than online courses. Several studies have identified the flexibility of online learning as a critical factor in program satisfaction and enrollment in online programs (Aalangdong, 2022; Larson & Sung, 2009; Moore, 2019). Similarly, a large proportion of those interviewed for this study stated one of the most essential features of online learning is the ability to attend class from anywhere. Hence, the particularly high representation of face-to-face programs in dropout data suggests challenges at home or work conflicting with regular attendance may be a factor in student dropout.

Figure 7: UG Enrollment



Online learning's flexibility contrasts with the constraints of face-to-face instruction, which requires physical class attendance in locations and times that may not always be convenient for potential students. According to research, female dropouts are primarily driven by family or childcare responsibilities, whereas male dropouts are prompted by economic necessity (IFC, 2022). Changes in family finances and situation and tuition pressures cannot be overlooked as significant factors in student dropout in the context of a developing economy like Ghana. Students enrolled in UG online programs where courses are primarily delivered online, with a limited number of in-person sessions on weekends or evenings, may find ways to accommodate other obligations within the flexible learning environment.

On the other hand, UG is a residential campus, and face-to-face instruction takes place during the day, Monday through Friday, which conflicts with most work schedules and leaves little time to take on additional responsibilities. The modalities' essential characteristics may account for the large drops in face-to-face instruction and the stable enrollment of online learning. For example, students with familial responsibilities and those who must work would be constrained by the physical attendance requirements of campus programs. They may be forced to discontinue their education, either temporarily or permanently. Hence, students' persistence in the online learning cohort may be due to the flexibility of online learning, which accommodates students' home and work demands.

The age of students enrolled in UG is comparable to that of traditional college-age students in residential institutions. For face-to-face instruction, 94.8% are under the age of 25, 75.8% are under the age of 23, 20.16 % are under the age of 21, and the upper age limit is 60 years old. However, only 58.8% of online learners are under 25, 44.77% are under 23, 21-year-olds constitute 13.8% of the student body, and those over 30 make up 11.1% *(see Figure 9).* The age frequency distribution for all enrolled students was moderately right-skewed, with higher counts of occurrences within the younger age demographic. On the other hand, the right skew in the online enrollment data detected the possibility of outliers, which were investigated during the matching process and determined to be a natural occurrence due to the adult admission policies.

In terms of total enrollment, 83.4% are under the age of 25, 68.3% are under the age of 23, and 21-year-olds make up 18.6% of the student body. For all UG enrollments, the IQR for age was 3, which is the distance between the first quartile, 21, which indicates that 25% of the data value for age is equal to or below 21, and the third quartile, 24, which suggests that 75% of the data value for age is at or below the age of 24. This outcome indicates that 50% of UG enrollments are between the ages of 21 and 24, with 25% under 21 and 25% over 24. Furthermore, the SD for age for UG enrollment of all students is 3.5, the SD for face-to-face instruction is 2.7, while those in online instruction is 4.7. This finding suggests that students enrolled in online instruction are older than those enrolled in face-to-face instruction.

Taken together, the data demonstrate the significance and popularity of UG's Mature Access Program[19]. The program provides a path back to education and certification for students who drop out at any point in their education journey. The only requirement for applicants is an official document proving the participant is over 25. Admission does not require proof of completion of lower-cycle education. The University of Ghana Access Course, offered in the UG learning centers on weekends, prepares applicants for the Mature Students' Entrance Examination. Those who pass the entrance exam are admitted to the university through the distance education department to online learning programs. Several alumni from the access program have pursued MAs and doctorates. Discussions with department officials regarding the

[19] https://admission.ug.edu.gh/applying/distance/entryrequirements

students admitted through the access program revealed its popularity and emphasized their persistence and strong performance. Therefore, what appeared to be outliers in the UG dataset were, in fact, the result of the mature access program's admissions.

Gender

Male students appear to have a slightly higher matriculation rate and a slightly higher representation in online learning while remaining constant in face-to-face instruction. Male and female students in all modalities are predominately single, with over 90% reporting their status as single. Of UG's total enrollment of 46,092, 20,474 were female, making up 44.4% of all enrolled students *(see Figure 7).* Female enrollment was significantly lower in online learning than in campus-based. Female students comprised 16,041 of the 34,918 students enrolled on campus, accounting for 45.94 % of enrollments, while 4,433 of the total 11,174 enrolled in online learning, accounting for 39.7 %. Female students in online learning are mainly between the ages of 18 and 33, with enrollment extending slightly to 39 for male students.

Furthermore, female students appear to have lower GPAs than male students, despite male students' slightly higher drop rate. In terms of degree objectives, 14,215 female students are enrolled in BA programs, 6257 in BS programs, and 2 in master's programs *(see Figure 7).* For male students, there are 16,821 in BA programs, 8,794 in BS programs, and 3 at the master's level. While female enrollment has not yet reached equity levels, it reflects parity in educational access.

These data findings highlight Ghana's Gender Parity Index (GPI), which measures gender parity across several development indicators. The score ranges from 0 to 1, "[a] GPI of less than 1 suggests girls are more disadvantaged...and a GPI of greater than 1 suggests the other way around." (*World Bank DataBank,* 2023). The GPI for gross enrollment measures the proportion of girls to boys enrolled in public and private schools. Although gender equity in UG enrollment is far from achieved, the male/female ratio reflects Ghana's efforts in expanding educational access across education cycles. For example, in 2020, Ghana's GPI for primary education was 1, secondary education was 1, and tertiary education was 0.9. (*World Bank DataBank*, 2023). The enrollment rate of UG is in line with Ghana's GPI index for the tertiary level.

The regional distribution of students, particularly online students, demonstrates the issue of digital equity and UG's methods of addressing the challenge. The UG data set shows the diverse regions students are from, with the Eastern (22.7%), Volta (17.2%), and Ashanti (16.4%) regions ranking as the top three in face-to-face enrollment. Regional online learning trends are higher, with 23.7% from Eastern, 18.6% from Volta, 15.3% from Ashanti, and 13.2% from the Central region. The UG learning center model allows UG to distribute courses through the centers where online is accessible to students, even in areas with inadequate connectivity *(See Appendix V).* As discussed in Chapter 3, digital access is a prerequisite for online learning. UG allows students who may not have home-based internet access to come to learning centers where they can connect to the internet and tutors. Although Ghana has one of the continent's highest levels of connectivity, access in regional areas remains difficult. In 2020, Ghana's average household internet access stood at 31.2%, with Greater Accra accounting for 52.3%. Outside of Accra, the figure falls to 38.9% in the Ashanti region, Central Region 34.3% and 19.9% in the Volta region, and 21.5% in the Upper East. According to the UG dataset, 70.8% (7,904) of online learning students live in areas where household Internet access is less than 39%, with only 12.8% residing in Greater Accra.[20]

Addis Ababa University

[20] Global Data Lab, Area Database (v4.2.1)
https://globaldatalab.org/areadata/table/cellphone/GHA/?levels=1+4&years=2021+2020+2019+2018

The dataset from Addis Ababa University consisted of students enrolled in online learning programs and face-to-face instruction at the graduate level. Figure 8 displays the characteristics of selected variables for UG, which are discussed further below. Appendix VI contains a descriptive statistics analysis for the US data set.

The data set reflects the online courses registered with the registrar's office as delivered in that mode and is not an exhaustive list of AAU's online courses. Unlike at UG, online learning at AAU is initiated and offered at the department level rather than at the university level. While some units have dedicated online programs, there are occasions when a course is unrelated to the program.

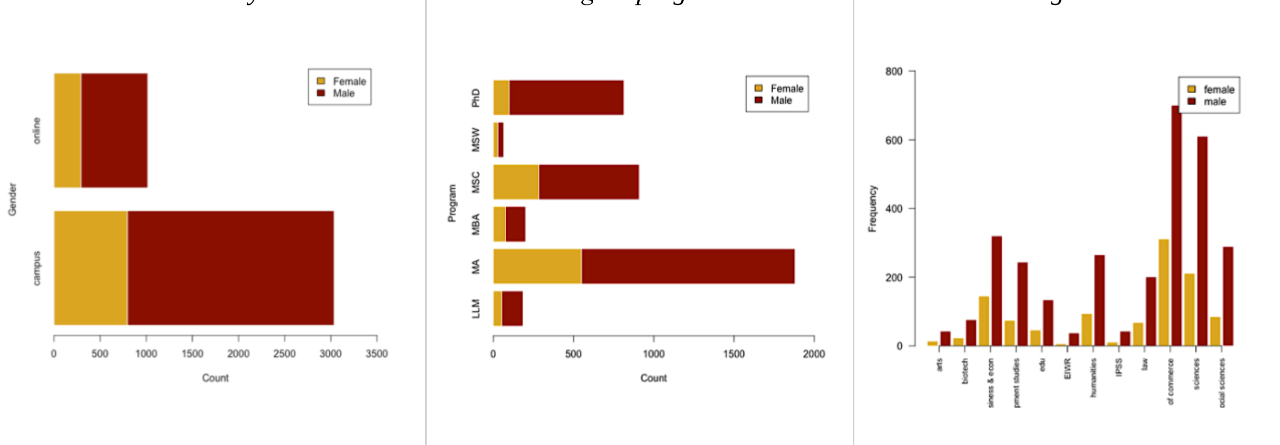
Addis Ababa University Study variables

The dataset for AAU had a total enrollment of 4,051, all at the graduate level. Of those enrolled in the 2018-2019 academic year, 3,036 were enrolled face-to-face, while 1,015. A cursory preliminary examination of the dataset revealed a significant irregularity, highlighting data management and collection issues not unique to AAU. A review of the age frequency revealed preteen enrollments. Although the enrollment of students in that age range cannot be dismissed outright, the possibility of outliers was investigated, given the number of observations. The examination revealed observations ranging from 1 to 11, which were determined to be caused by the date of birth data entry challenges discussed in Chapter 3.

Aside from the abovementioned inconsistency, the AAU dataset depicts the institution's evolving mandate and mission to increase graduate education. The GPA of enrollments across the three datasets indicates a higher average, with the full dataset mean of 3.5 and median of 3.5, campus enrollment of 3.2 mean and 3.5 median, and online mean of 2.7 and median of 3.2. Like the UG dataset, online learning has a lower GPA mean than face-to-face. The frequency distribution of CGPA on a 4.0 scale was asymmetrical for all enrolled students, with a high distribution of data, higher CPGA, to the right tail, and a long tail on the left. The distribution is skewed to the left by -1.65, indicating significantly more values above 3.0 on the GPA scale. Only 7.6% of the full data set fell below 3.0, while 79.7 % fell above 3.2%. For campus enrollment, 13.9% had a GPA of less than 3.2, and 75.3% had a GPA of greater than 3.2, whereas, for online learning, 34.5% had a GPA of less than 3.0, and 46.8% had a GPA of greater than 3.2 *(see Figure 9).*

Figure 8: Addis Ababa University Enrollment

Modality | *Degree program* | *College/school*



While face-to-face graduate programs primarily train faculty for regional universities at the PhD level, online graduate programs serve working professionals seeking additional accreditation primarily through MA level programs. The MA level has the highest enrollment rate, accounting for 46.4 % (1,880) of all enrollments, followed by MSC 22.4 % (909) and PhD 20.1 % (813). The School of Commerce, which has historically served as the unit for continuing education for working adults, has the highest enrollment at 25% (1,011) *(see Figure 8).* The other units with notable enrollment include the Sciences 20.3% (821) and the School of Business and Economics 11.5% (465), further highlighting the dominance of MA level training in the professional fields.

The difference in enrollment in programs and units between online and on-campus students further emphasizes this two-track graduate level training. Campus enrollment reflects the total enrollment figures, with the MA and MSC programs with the highest enrollment at 35 % and 26.4 %, respectively. The enrollments are mainly in the sciences, such as water management and information studies, in humanities in areas focused on political science and social work, and in development studies. These enrollments reflect national development and political priorities and the general perception that advanced degrees are critical for growth in the civil service. When it comes to online learning, however, the School of Commerce leads the way with 79.1 % (803), followed by the School of Business and Economics at 17.6% (179).

Similarly, the MA programs have the highest enrollment in the online modality at 69.0 % (700), and the MBA program has 18.9 % (192). These online enrollment patterns are consistent with overall enrollment patterns, indicating that online learning has created a new path to certification for those unable to attend face-to-face programs. Working professionals have traditionally enrolled in evening courses at the School of Commerce to pursue advanced certification while working. The School remains AAU’s life-long learning unit, and in addition to the recent establishment of the School of Business, which offers both MBA and EMBA programs, this pattern appears to have migrated online.

The data set’s age distribution reflects the prevalence of adult enrollment. The frequency distribution of age for all enrolled students shows a higher observation within the mid-thirty age range, with a steep decline to the right and left tails, which corresponds to students pursuing graduate degrees. The average age of AAU students was 35.3 years old, with a maximum of 70 years, 68 for online students, and a median of 35, reflecting the dataset's concentration of adult enrollment. The age mean for online enrollment was 37, with a median of 38. This data suggests working adults in their mid-career are returning to school for additional certification.

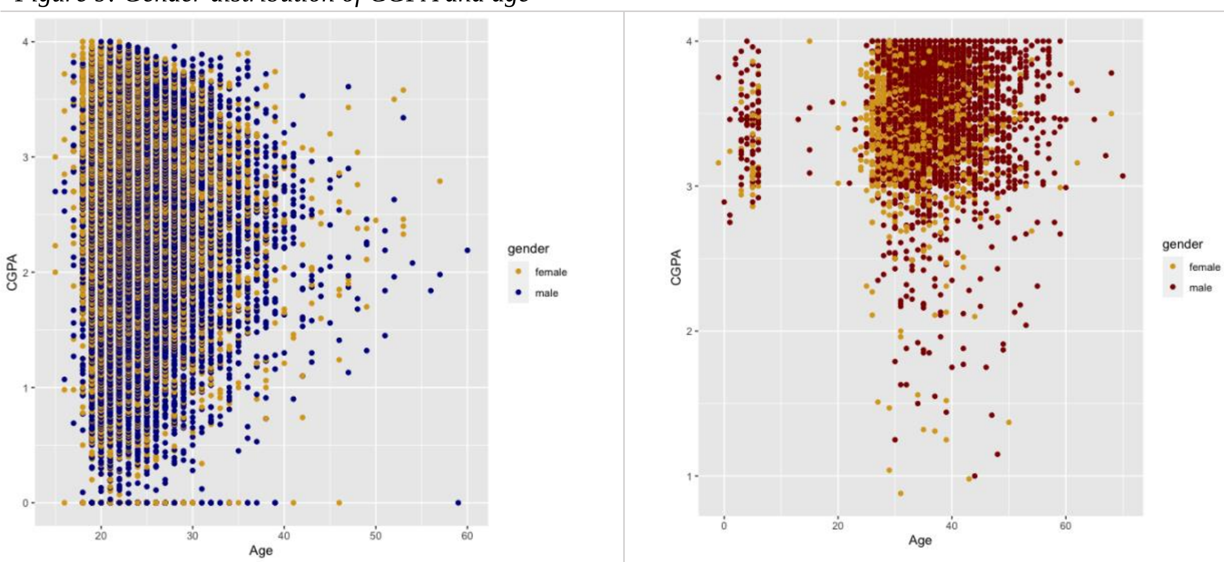
The dataset also indicates most enrollments were in their program's early stages. The frequency distributions of overall enrollment and face-to-face and online learning enrollment were right-skewed, indicating higher enrollment at the early graduate levels. The average year of enrollment was a year and a half, with a median of one year pointing to a larger representation of master's level enrollment. While online programs were three years, face-to-face programs were six years, suggesting that online programs were mainly at the MA level and face-to-face programs included PhD level training. The mean of a year and a half, combined with the higher proportion of MA level enrollments, suggests that most students were in MA level programs and in the early stages of their training.

Gender

The AAU dataset had a total enrollment of 4,051, with female students comprising 26.9%, significantly lower than UG enrollment proportion. Male enrollments outnumbered female enrollment across all modalities by at least two to one. In disaggregating across modalities by gender, male students were 73.1% (2,963) and 26.9% (1,088) were female in the full dataset. While for online learning, women accounted for 28.8 % (292), men accounted for 71.2% (723), while men accounted for 73.8% (2,240). For face-to-face instruction, women were 26.2% (796). These figures are significantly lower than the education participation rate in UG, which was close to parity at over 45% *(see Figure 7).* Ethiopia's GPI in primary education is. 0.9, similar to Ghana's, which is at 1. However, it drops significantly to 0.60 (2018) at tertiary and tertiary gross enrollment for women is 7.8% (2018) (*World Bank DataBank*, 2023). The education cycle data for Ethiopia indicates although female students are well represented at the primary level, their participation drops precipitously beginning secondary level.

Female education interruption at the secondary level contributes to low female enrollment in tertiary education. Despite 55 public universities and 117 private universities, colleges, and vocational training institutions throughout Ethiopia, tertiary enrollment rates remain remarkably low. Furthermore, the attrition rate for female tertiary level students in Ethiopia ranges from 13% to 33% (Asfaw, 2012). Although women face many social and economic challenges in accessing and completing tertiary education, a recent study pointed to life events, childcare responsibilities and environment as among the drivers of female dropout (Ali, 2019). These caregiving responsibilities primarily fall on women, making it difficult for them to continue their education within the constraints of face-to-face instruction. The challenge of physically attending class is reflected in the 26.2% female enrollment in face-to-face instruction at AAU. However, unlike UG, online learning may not be the answer to AAU's female enrollment and attrition problems.

Figure 9: Gender distribution of CGPA and age



University of Ghana

Addis Ababa University

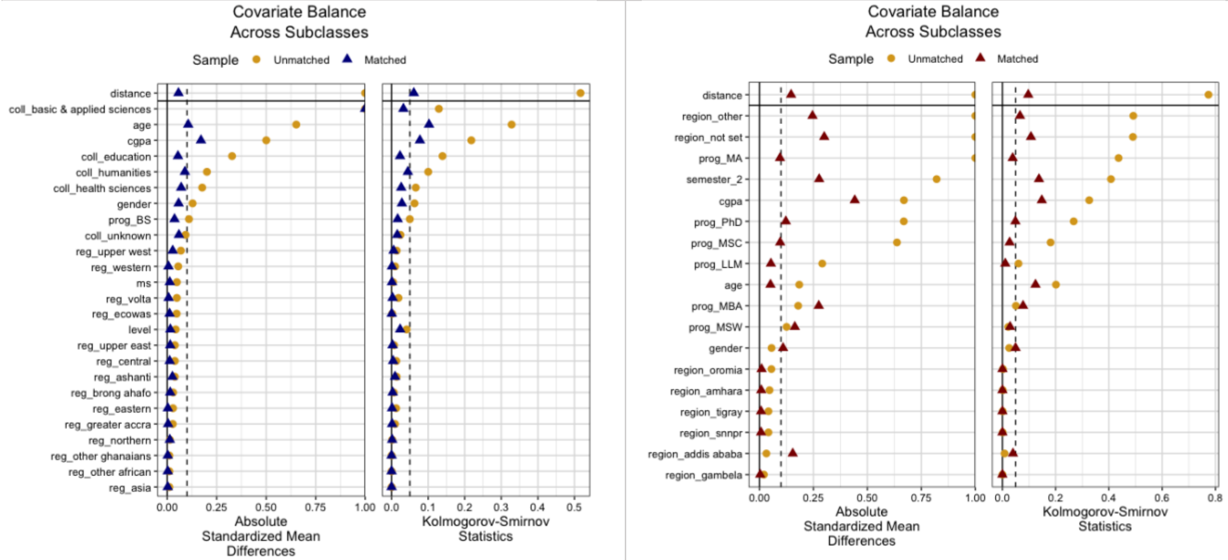
Female enrollment in online learning at AAU is also low, at 28.8 %, which is not much higher than face-to-face instruction. Furthermore, unlike UG, AAU lacks regional learning centers capable of delivering instruction and internet access for students to participate in online learning. Due to Ethiopia's relatively low national ICT capacity, internet access is generally unpredictable and, in most cases, unavailable outside Addis Ababa and a few other major urban centers. Although some AAU online learning students have identified other regions as their hometowns, the data does not specify whether online learners connect from their home region or Addis Ababa. However, given the limited connectivity outside of the capital, those enrolled in online learning are almost likely in Addis Ababa and chose the online mode for other reasons.

Propensity score matching

University of Ghana

Propensity score matching was conducted using the *r* package *Matchit()* to estimate the effect of treatment on those enrolled in online learning (see Appendix VI for code and output). Before matching, logistic regression was used to view and understand the data imbalance that PSM seeks to address. The model consisted of modality (treat for online learning and control for face-to-face instruction), CGPA as the outcome, and the variables were age, gender, marital status, level, region, college, and program. The *Matchit()* formula was used with the method set to NULL, and the results indicated there was room for improvement based on standardized mean differences that were not entirely within the range of zero and variance ratios that were well above one. The initial matching specification used a one-to-one, nearest neighbor method, which matched the propensity score without replacement using logistic regression of the treatment on the covariates. However, this matching specification resulted in poor balance.

Figure 10: Covariate Balance Across Subclass UG and AAU



University of Ghana Addis Ababa University

The second attempt used the subclass method with 6 classifications to estimate the treatment effect of the treated (ATT). Subclass method performs classification based on propensity score where "[t]reatment and control units are placed into subclass on quantiles of the propensity score" (*R Documentation*, n.d.). The propensity score was estimated using logistic regression, which used all treated and control units and yielded an acceptable balance, as indicated in Figure 10. After matching, except for CGPA, which had slightly higher standardized mean differences, all other covariates were under 0.1. However, the eCDF statistics for all covariates indicated improvement and were close to zero, and there was a significant improvement in the variance ratio, which was reduced to under 1. These outputs indicate an acceptable balance for the model. Appendix VI contains complete balance visuals and tables for UG and AAU.

The *marginal effects()* package using *comparisons()* function was used to estimate the treatment effect and standard error. For estimating marginal effect, a linear regression model with *lm()* was used with CGPA as the outcome, the treatment and covariates with interactions as predictors, and matching weights. The estimated effect was 9.2% (SE= 0.046, and p= 0.044), which indicates that the average treatment effect of treatment, online learning, for those enrolled in online programs at UG was an increase in CGPA by 9.2% and was statistically significant *(see Table 4)*.

Table 4: Estimated effect of UG and AAU

	Term	Contrast	Estimate	St. Error	z value	Pr(>|z|)	2.50%	97.50%
University of Ghana	Treat	1 – 0	0.0922	0.0461	2	0.045	0.00206	0.182
Addis Ababa University	Treat	1 – 0	0.207	0.0625	3.3	<0.001	0.0841	0.329

Addis Ababa University

The AAU matching process was similar to the UG process discussed above. The model consisted of modality (treat for online and control for face-to-face), CGPA as the outcome, and the variables were age, gender, region, program, and semester. The r package *Matchit()* was used to match units based on propensity score (see Appendix VI for code and output). Logistic regression was first used to detect an imbalance in the data, followed by running *Matchit()* with NULL for the method to view balance. The output indicated room for improvement based on the standardized mean differences and the variance ratio.

The first matching attempt used a one-to-one, nearest neighbor method, with matching based on the propensity score without replacement using logistic regression of the treatment on the covariates. This matching specification resulted in poor balance, and the second attempt used subclass. Using the subclass method with 6 classifications, all control and treated units were matched, and there was an improvement in balance with standardized mean at or near zero. The propensity score was estimated using logistic regression, which used all treated and control units and yielded an acceptable balance, as indicated in Figure 10. After matching, outputs indicate an acceptable balance for the model. Appendix VI contains complete, balance visuals and tables.

The *marginal effects()* package using *comparisons()* function was used to estimate the treatment effect and standard error. For estimating marginal effect, a linear regression model with *lm()* was used with CGPA as the outcome, the treatment and covariates with interactions as predictors, and matching weights. The estimated effect was 20.7% (SE= 0.0625, and p= 0.001), which indicates an average treatment effect of 20.7% for those enrolled in online programs in AAU, and it was statistically significant *(see Table 4).*

Summary

The chapter presented and discussed the results of the quantitative study comparing the effectiveness of online learning versus face-to-face instruction at UG and AAU with CGPA as a measure of learning outcome. Descriptive statistics were used to examine the data and connect the dataset to the institutions' characteristics and the role of online learning. Online learning at UG is at the undergraduate level and an overflow management mechanism where required courses with higher enrollment are converted and delivered online. On the other hand, AAU's online learning was at the graduate level, with MA and PhD programs targeting working professionals seeking additional credentials. While both intuitions had enrollments of students that were not within the traditional college age demographic, for UG it was a result of the Mature Access Program, while for AAU, it was part of its graduate level enrollment of working professionals.

The descriptive data also emphasized national gender equity issues. Ghana's GPI score for tertiary education is 0.90, close to one, indicating equal access for men and women. This score is reflected in undergraduate enrollment data, with the institution approaching gender parity with 44 % female enrollment. However, the tertiary enrollment rate in Ethiopia is less than 25%, while AAU is at 26%. There was no attrition data available, however, the UG data contained over 1,000 observations with zero GPAs, and non-passing GPAs with face-to-face instruction accounted for 95% of all UG dropouts. Whereas AAU data showed no dropouts. Many of these issues link to the challenges of attending brick-and-mortar classrooms, particularly for students with multiple and competing priorities, of which many are female.

Causal inference analysis was performed on UG and AAU separately in *r* using the *Matchit()* package. A review of UG and AAU data sets suggests face-to-face instruction delivers higher learning outcomes; however, online learning accounts for less than 25% of total enrollment in both UG and AAU. Hence, leveraging matching allowed a comparison of learning outcomes based on student characteristics. The propensity score matching found that online learning had a greater positive effect on learning outcomes, as measured by CGPA, in UG by 9.28% with a standard error of 0.046 and P value of 0.044, and to a higher degree AAU by 20.7% with standard error of 0.0625 and p-value of less than 0.001. The PSM results for AAU and UG were statistically significant. The implications of the results are discussed in Chapter 6.

CHAPTER 6 | Qualitative Analysis

Introduction

This chapter presents the qualitative findings of the sequential mixed-method study on online learning in UG and AAU. The research employed a mixed-method approach with a sequential study in which the quantitative analysis was completed first to allow the results to inform the qualitative research. The qualitative research question asks, "How does the deployment and implementation of online learning at the University of Ghana (UG) and Addis Ababa University influence learning outcomes?" Responding to this question provides an opportunity to contextualize and elaborate on each institution's unique approach to online learning deployment and the potential impact of the process on learning.

The chapter is organized with a section for UG and AAU, presenting findings from the qualitative portion. This organization was selected to emphasize the decision to study each institution independently to build an understanding of the national and institutional context of the deployment of online learning.

Qualitative

The qualitative portion of this investigation was designed as a dual case study to support an understanding result of quantitative findings. To that end, the qualitative section responds to research question #2: *How does the deployment and implementation of online learning in AAU and UG influence learning outcomes?* The quantitative study found online learning had a greater positive effect on learning outcomes in UG and AAU than face-to-face instruction. AAU has a 20.7% estimate, and UG has a 9.2%. The case study method aids in contextualizing and interpreting the increased efficacy of online learning at UG and AAU. It investigated each institution's unique framework for online learning deployment to identify factors that explain the disparity in outcomes. Appendix VII contains the qualitative instruments, including interview and focus group questions.

The case study findings indicate that the differences in the deployment of online learning between UG and AAU are influenced by the historical development of higher education within each nation. These developments can be framed by two issues: the scope and mandate for higher education at the time each institution is founded and the development of institutional infrastructure. Moreover, while both institutions lack national and institutional level mandates and guidelines for online learning, each institution's deployment aligns with the national education mandate.

University of Ghana

Even though UG was founded as, and continues to be, a national flagship teaching and research institution, educational access was integral to its founding mandate. In the early years, the development of the regional learning center model expanded educational access across the country and laid the groundwork for online education. UG began offering academic programs and established a physical presence outside of Accra to extend its educational services to a broader population nationwide.

> "[The] University of Ghana has a distance learning Unit in ten regional capitals and all the regional capitals run the same program with the exception of Accra, that has some other programs (*Learning Center II*, personal communication, July 22, 2021)."

As discussed in the methods chapter, continuing education pathways such as workers' colleges, learning centers, and degree programs played an essential role in the history of UG, particularly in the development of the Department of Distance Education, which currently houses online learning *(see Appendix V).* This regional expansion was closely related to the goal of providing working adults with education and certification to participate in the workforce.

The effort to reach adult learners predates the formal establishment of UG in 1948. The appointment of an Oxford resident tutor in 1946 to carry out Extra-Mural Studies can be considered the beginning of university-based adult education in Ghana.

> “The Department of Adult Education and Human Resource Studies could trace its origin and development to February 1948 when the Department of Extra Mural Studies was established prior to the establishment of the University College of the Gold Coast (*University of Ghana: AE/HRS*, 2022).”

Shortly after, in 1952, the unit was renamed the Institute of Extra-Mural Studies and was later renamed the Institute of Public Education. By the 1960s, UG established Worker’s Colleges to provide part-time education and certification to working adults by establishing what are now known as Learning Centers *(see Appendix V).* As noted in an interview, the evolution of this system led to the UG School of Adult and Continuing Education, which houses the Department of Distance Education

> “…we’ll call them workers colleges. So, they would work as colleges under the Institute of Adult Education. And when the transition was made to continue, and distance education, all those regional centers, and there are 12 of them, were transformed from just being workers’ colleges to the University of Ghana Learning centers. And the focus then became distance education, tutorials and distance education in whatever format we have it, including diploma and degree holders…(*Distance Learning/Sakai*, personal communication, July 27, 2021).”

The UG Learning Centers served two functions: they provided instruction and training while also identifying regional education needs and priorities. They were tasked with developing strategies to meet the educational needs of their sector by incorporating UG courses and, in some cases, developing stand-alone programs tailored to the region.

> "… ours is more of community engagement; we send educational programs to the community and get into the content. And try to interact with the people [to] identify the educational needs within the community, and we design programs for them. So, more or less, an extension wing of the University of Ghana as other universities in other parts of the world are noted for (*Learning Center I,* personal communication, July 10, 2021)."

The learning center model, now an essential online learning conduit, was mandated by a national and institutional policy that prioritized making education accessible to working adults, particularly those living outside of Accra. The most recent Education Strategic Plan expands on this goal, with the first policy objective outlining "[I]mproved equitable access to and participation in inclusive quality education at all levels," tasking tertiary institutions with increasing "numbers of admission places available to meet all needs."(MoE, 2017, p. 58). Given the challenging fiscal budget, one of the strategies is leveraging technology to create space for increased tertiary admissions. Thus, the programs and infrastructure developed by UG to fulfill the post-independence mandate to increase educational access serve as the foundation for expanding on that mandate through technological integration. The UG Department of Distance Education (DDE) website provides a concise history of distance learning from correspondence to online:

> "The Department of Distance Education of the School of Continuing and Distance Education began as the Correspondence Unit of the then Institute of Adult Education in 1973….[t]he Unit was later christened the *Distance Education Unit* to correspond with the changing trends…[t]he first Coordinator to organize the Distance Education Centre for the Distance Education Programme [was appointed] in 1995. During this period, four Departments, namely English, Sociology, Political Science and Religions, agreed to offer their courses through the distance mode and so started to develop their courses…In 2006, the programme was brought to the then Institute of Adult Education…[and] a University of Ghana Distance Education Implementation Programme was established...[t]he committee reorganized the programme and started training new course writers in Economics, Geography and Resource Development, Sociology and Linguistics…In 2006…History and Social Work were included in the Humanities as well as BA (Administration). The Bachelor of Arts Degree programme by Distance Education was launched in November 2007…[c]urrently courses are being offered in B.Sc. (Nursing) at Level 200 as well as BA Information Technology…. (*University of Ghana/DDE*, 2022)."

UG's distance learning program, which began as a correspondence program, later became distance learning with paper-based modules. Paper modules gave way to digital modules as technology advanced, and UG began to integrate technology to deliver lessons and learning materials.

> "The programme (distance education programs) is currently using the University Learning Platform called Sakai to deliver some of the courses alongside the print

> materials and face-to-face tutorials in 9 learning centres, namely Accra, Koforidua, Bolgatanga, Sunyani, Tsito, Tamale, Wa, Takoradi and Kumasi (*University of Ghana/DDE*, 2022)."

Interviews revealed how technology was integrated into UG distance education programs. The correspondence model gave way to the paper-based module/tutorial model, where students were given printed modules and attended tutorials during the weekend for in-person lectures at the learning centers (Aalangdong, 2022). Technology was first integrated into the paper/tutorial model in 2014 with the ICT-based Distance Education Project. The project introduced Sakai, a digital learning platform for distance learning, and digital technology to learning centers. Computer laboratories for students, a video conference center connecting learning centers to the main campus via the Vodafone National Fiber Backbone, and a smart classroom are among the technological investments made in the learning center through the project (University of Ghana, 2014).

As a result of the Distance Education Project, UG transitioned from a paper/tutorial model to a hybrid model in which learning materials were delivered via technology, but weekly in-person lectures were retained (Aalangdong, 2022). This hybrid model gradually integrated digital technology, but COVID accelerated its full integration.:

> "…we were running a hybrid system, where [we] will use the Sakai to engage students. And then, during the weekend, students will be at the Centers for the face-to-face. And then, in 2020, a semester before the COVID-19 lockdown, we piloted a full online what we call x module. The essence was that we have 11 centers scattered across the country. And we don't have the budget to transport lectures to meet all these students. So, we did a proposal, and it was favored by

> the powers that be. And that was how come we were the first to bring the lectures to teach undergraduate students in D (distance learning). That has not been done in Ghana. The practice has been team teaching. Students don't know these students don't know their lectures. But we did that. And so lecturers meet students, four times a semester, and then the tutors also do that…which has improved the quality of our tutorial system (*Department of Distance Learning*, personal communication, March 2, 2023)."

Distance learning is now primarily online, which has altered some of the processes involved in developing modules. There is a greater push to incorporate more engaging materials and transform the assessment process.:

> "…we make [modules] when the program started, they started developing modules, you know, the traditional modules texts. Then when the collegiate came and then the hybrid system came in, they changed it to what you call Interactive Mode modules, where you have power points, I call it power loops because it's really packed…[a]nd then you also give us the study guide…but our study guide is very comprehensive…we also take what we call question bank, multiple choice questions about 500. So that over time, we'll be using it to do a continuous assessment, not exams. So, you have to give us all these deliverables. And that is what we load on the system (*Department of Distance Learning*, personal communication, March 2, 2023).

Despite UG's plans and processes for online learning delivery and an extensive network of learning centers, fully utilizing the digital system remains a significant challenge. Despite investments in physical infrastructure, UG's digital infrastructure and the process of deploying

ICT resources represent a challenge to the deployment of online learning. The ICT-based Distance Education Project was an attempt to digitize distance learning rapidly; however, several centers were excluded, primarily because the buildings housing the learning centers were in poor condition and the institution did not own the structure (Aalangdong, 2022). Furthermore, technology is a rapidly changing field, and much of the project's investment is outdated. Finally, the UG's ICT deployment strategy is heavily centered on the main campus in Legon, with networking and access to and from learning centers routed through Legon. This centralized network infrastructure poses a challenge for those in areas with limited connectivity due to a regional digital divide. Much of the discussion in the interviews and focus groups revolved around the technological difficulties of accessing and delivering online learning.

> "You know the exams are set by lecturers in Accra, and they pretend as if Accra is the whole of Ghana. They forget that there are some remote areas in the country where they don't have access to the internet; somebody has to travel at maybe one mile or two miles from where he or she is just to get access to the internet. And here is the case, a lecturer sets an exam for three or four hours; says the exam is going to start at maybe 8am in the morning and end at 12pm. And here is a student who is somewhere in a remote area and didn't get the message early. By the time he gets the message, the exam is over; and he wants to retake it, but we don't allow it (*UGLC Focus Group*, personal communication, August 3, 2021)."

Participants recount workarounds to the connectivity challenges they faced during the early deployment of the ICT-based Distance Education Project:

> "One, internet connectivity issues; and then sometimes they are not populated on the Sakai page at that moment, so they can't access those materials. So, the easier

way out was for us to give them materials on a hard drive. So, you come, and then for your level, you just copy everything. So the IT guys organize a trip to Accra…brought the drive, and then the person in charge of materials would just upload everything unto the drive, and…then when the students come, instead of going to download it themselves, they just go to the IT guy…[b]ut we make sure they have already paid up to them before they can access (*UGLC Focus Group*, personal communication, August 3, 2021)."

Furthermore, according to IT staff in the regions, learning centers do not have their own internet connection and instead connect to the internet through the main campus.

"There are some challenges. If there is a power outage on campus or the services are overstretched there, it affects us. If we had the setup at the center or at each center, it would have enabled us to give faster services to students. Aside from that, there are fiber cuts, and we take our feed from…which is like 30 minutes from [us]. The fiber optics are in the ground, and so at times, fiber cuts make the center go off for a long time…(*Learning Center II*, personal communication, July 22, 2021)."

This configuration of the technology infrastructure causes significant internet downtime, with learning centers experiencing interruptions due to outages at the main campus and service interruptions at local sites. Sometimes, these interruptions occur during an exam, and students are given an incomplete and must retake the exam.

"Internet…is not all that reliable and so mostly when we are writing exams, we encounter a lot of internet challenges. Sometimes in the case of the students writing, the internet can just go off. Sometimes too, it wouldn't be off, you will see that the internet is on, but you will not be able to connect the apps….(*Learning Center II*, personal communication, July 22, 2021)

Cloud technology is also not in use, which means that servers in learning centers are mirror serves. All authentication is managed at the main servers on the main campus, including blockchain, which is not decentralized and is duplicated across all centers.

> "…so, most of the services are authenticated back on campus in Legon; the authentication servers are all back on campus, so that is why we need to connect through them. For example, our WIFI authentication servers are all back on campus, so we need to connect back to them. The BNS servers are all back on campus, and so our connections always reroute back to campus, and this affects all the centers. (*Learning Center II*, personal communication, July 22, 2021)."

While UG has developed the academic methodology and process for mounting online learning, the challenge of expanding online learning appears to be technological. Despite IT staff clearly articulating system flaws and identifying solutions in the context of local connectivity, it was unclear the extent to which national infrastructure and connectivity were factored into UG's IT deployment for online learning. There was also ambiguity in the upgrades, adjustments, and maintenance performed on ICT infrastructure at UG between the introduction of digitalization in 2014 and now. As discussed in previous chapters, Ghana's connectivity is among the highest on the continent, and while there are regional challenges, connectivity has improved.

> "…maybe the last five years [connectivity] has really, really improved…If you go to my village…if the person is online five years ago, you would have to go and stand at a particular location where you will get a strong network. But now they

> are in your rooms, and you're calling. [s]ome even call by video (*Tech Experts Ghana*, personal communication, July 26, 2021)."

Based on the dominance of technological issues and challenges during interviews and focus groups, the current networking system of UG is susceptible to multiple connectivity challenges. The centralized infrastructure, which relies on Legon for internet, networking, and other services, causes disruptions during power outages in either the main campus or the learning center, resulting in users failing to access the system. The technical challenges are partly due to low connectivity but primarily due to the approach to IT functions that heavily relies on UG main campus protocol that does not make allowances for the unique requirements of the online learning platform and low connectivity environments. The centralization of functions such as logins and the lack of cloud computing capacity exasperate connectivity challenges and create a challenging environment for adopting and expanding online learning.

According to the UG case study findings, online learning at UG evolved from a system that has developed experience and expertise in delivering educational services across Ghana. The interconnectedness of learning centers and distance learning provided a foundation for online learning as well as the groundwork for a pedagogical process that adapts courses for virtual delivery. The integration of technology, however complex, is ongoing, but workarounds appear to have limited its impact on learning. Therefore, it appears that the positive effect of online learning is due more to the pedagogical evolution of distance learning and despite the ICT infrastructure of UG.

Addis Ababa University

Addis Ababa University was founded as a flagship institution by Emperor Haile Selassie "to provide the youth of Ethiopia with a sound academic background in the fields of Arts and

Science, leading to further professional studies abroad (University College of Addis Ababa Bulletin in Hapte, Aklilou, 1961, p. 28).” Due to the general scarcity of primary and secondary schools at the time, it was never intended to be a public institution. For instance, in 1952, the entire student population in Ethiopia numbered 60,000, mainly in 400 primary and 11 secondary schools (Teferra & Altbach, 2003). Hence, access was not a primary consideration in establishing AAU, which serves as a framework for contextualizing the deployment and delivery of online learning at AAU. Despite expanding its programs and capacity since its founding, AAU remains a high-ranked higher education institution centered in Addis Ababa.

In terms of limited access and disciplinary focus, online learning follows AAU's established institutional pattern. The Addis-centered legacy of AAU has hampered the development of infrastructure and facilities for delivering educational services across Ethiopia. The lack of expansion beyond the capital in the early years of its founding could be attributed to a lack of qualified candidates as a result of limited primary and secondary education. Still, it could also be attributed to a lack of vision in developing and designing relevant and appropriate programs for the larger population. Although AAU had colleges and programs outside of Addis Ababa at various points in its history and enrolled students from all over the country, its operations and programs were firmly based in the capital city. Similarly, while adult education was, and still is, an important component of higher education in Ethiopia, it was also confined to the School of Commerce and various evening programs at AAU, all based in Addis Ababa.

The lack of institutional guidance and direction and its role within the university is the primary feature of online learning at AAU. Although there is a distance learning unit that formally offers distance learning online classes, the vast majority of online courses are hosted by departments and schools. The development of online learning courses is left to the lecturer and the home department due to the lack of institutional or national benchmarks. Most faculty are hesitant to participate in online learning, which could be because there is no mandate or support from higher up in the institution, resulting in a disjointed and compartmentalized online earning landscape. AAU's substantial institutional investment in IT resources is a second feature of online learning, though the country's underdeveloped ICT infrastructure limits its reach. Ethiopia has the lowest internet penetration rate at 25% in 2022, posing a challenge for those outside the city to participate in online learning effectively (*World Bank DataBank*, 2023). It was difficult for IT personnel to answer to what extent the internet was available outside Addis Ababa:

> "…it's difficult to answer because, as far as I know, when you go to different regions or rural areas in some areas, they don't have any internet coverage (*AAU Technology*, personal communication, March 8, 2023)."
>
> "*Woreda* net extends outside of Addis and even that is very poor. There are about 1000 *Woredas* in the country…and out of that, only about 120 were connected (*AAU Faculty I*, personal communication, December 21, 2022)."

Thus, the delivery of online learning at AAU can be described as siloed and fractured yet innovative and technologically sophisticated.

According to the case study, while there is no centralized resource and support for mounting online learning courses, the university has invested heavily in providing technological support for its education mission. The central IT office, located on the main campus, maintains, and secures all the institution's technologies and software.

> "…we [have] data centers, connectivity servers…we have large cloud systems, it's a private cloud system, it's a NetApp Solutions…all systems…which control the inputs accessed from different colleges are stored here…. colleges high-speed

internet connectivity. Plus, all our campuses are wireless, it's Aruba Solutions…so it's reliable and which has strength [and] capacity…. [i]f the students they don't have laptops also, we have…VDI, virtual desktop environments…[i]t's also a cloud systems storage, which the main storage was installed in our data centers. Simply we put some client computers on dormitories, libraries and...dormitories, libraries and…students have their own usernames and passwords…they can put their data…we give them some storage like two GB three GB for specified times.

"… we have different standalone servers for different mechanisms…[when] the university [administers] different international tests like GAT, GRE …we have different separate servers to use for these things. Plus, we have different separate high-capacity servers….used for high-performance computing…our data centers are big, always we are scaling up…now we are working on the Disaster Recovery Center. We've got another data center at Lideta campus… compare Addis Ababa University data centers, when you try to compare it with the other big industry data centers, these data centers are much bigger, more modern data centers and network environments."

The IT office is also charged with ensuring connectivity on the campus.

"…[we are] using a large capacity leased double line for redundancy and security…the government, it gives us more privilege because we have larger bandwidth…almost all the bigger colleges they have their own connectivity…they have a VPN connectivity…the payment for the VPN is much higher than the internet connectivity payments. So, the government always [supports] us

> financially…almost more than 75% of the University budget are taken by the buildings and ICT. Mostly because the ICT technology and even the ICT environment, especially the environment [costs] so much money.

Academically, the approval for mounting online courses rests with the department. Once a faculty informs the department of their intent to develop an online learning course, the department communicates their approval to IT staff in the department. Since all campus units have an internal IT capacity, that office often takes charge of providing technical support, however, in the event the technological needs of the course are beyond the capacity of the unit IT personnel, the support is provided by the central IT office.

> "…when one professor wants to give a course online first, it is communicated with its departments. So, after his department acknowledged that this course must be given online so the department communicates with the campus ICT personnel. As soon as we give different credentials to campus ICT, ICT personnel, if this thing is over their capacity, they communicate with us (*AAU Technology*, personal communication, March 8, 2023).

The technical support provided by IT, either locally at the campus or from the central IT office, includes:

> "…we provide the environment…it's the servers, the storage and so on. Next [we help them decide] which technology [to] bring to the university because there are so many learning management systems out in the field….some of them are open source, some of them are commercials. In that case, we choose and develop, or we adapt and adopt these technologies. So, for now, we're using Moodle and eFront. So, after we customize and we install this technology or this learning management

> system in our data centers, the next thing is we give training for the teachers and the students. So, we handle the overall technical [but] only technical (*AAU Technology*, personal communication, March 8, 2023).

It's interesting to contrast the technical support available for mounting online learning with that available for course preparation. Instructors are generally left to their own devices in converting their face-to-face instruction course for online delivery. Furthermore, there does not appear to be institutional support for instructional design or general guidelines and procedures for developing online courses.

> "I have given [instructional design training] this campus alone. I don't know 3 or 4 trainings on how to use Moodle. The best way is to use it more probably for the sciences. Obviously, without the audio-visual recordings, just electronic materials, the references, and so forth…[b]ut, there is no so instructional design expert on campus…like a resource person that we can use….they might have one in this kilo (*AAU Faculty I*, personal communication, December 21, 2022)".

However, faculty with advanced online learning expertise appear to serve as *de facto* leads for their unit and department in online learning by providing academic support for mounting online courses from selecting and securing LMS to instructional design.

> "…but the main campus…has its own learning management system based on Moodle. But we also have one at the Arat Kilo campus that we use internally within the compound. I'm also familiar that the Information science, the Department of Information and Science, has its own LMS system. There may be others on campus that I'm unaware of, but there are multiple routes…(*AAU Faculty I,* personal communication, December 21, 2022)."

AAU online courses were exclusively offered at the graduate level at the time of data collection for this study, even though there was a demand for enrollment at the undergraduate level[21]. This shift may be due to AAU's mandate to serve as a graduate training ground for the staff of the over 34 public universities established in the last 20 years.

> "…the ministry differentiated the 40 universities and discovered Addis Ababa University was categorized as a research university. When you think about a research university, that means you will focus more on research and graduate studies. That means having less undergrad and maybe, in the future, no undergrad studies (*AAU Faculty II*, personal communication, January 10, 2023)."

It is unclear, however, whether the prevalence of graduate-level training in online learning was designed to meet this challenge or if it is an effort to integrate online learning into AAU's teaching mission.

Therefore, online learning in AAU has developed and continues to expand from within departments and schools. Although there is little academic guidance at the campus level, there is a significant investment in digital technology to support online learning, from hosting to training to lecture recording and animation. It was unclear whether the lack of campus-wide guidelines on online learning contributed to faculty declination to participate or whether faculty opposition to the modality, whether passive or explicit, contributed to a lack of institutional-wide leadership.

Moreover, similar to AAU's face-to-face instruction, online learning has limited reach and access, with a strong focus on graduate-level training in business affairs and areas deemed of national importance, with enrollment populated by working adults. AAU's lack of physical infrastructure in the regions to host the delivery of its educational services, combined with

[21] AAU online offerings now include undergraduate courses.

Ethiopia's underdeveloped ICT infrastructure, has limited the reach and accessibility of its online learning programs. Hence, despite expanding its academic offerings and digital technology, AAU's online learning remains strikingly similar to its educational services at its founding, with limited access concentrated within Addis Ababa.

Summary

The qualitative dual case study investigated whether the deployment of online learning between UG and AAU accounted for the effect found in the quantitative analysis. The UG and AAU were founded around the same time, and the trajectory of each institution was determined by the national historical and social context at the time of their founding. The case study investigated the impact of this context on infrastructure development which now influences access and reach of their educational programs, including online learning.

UG and AAU were founded as flagship teaching and research institutions. The impending end of colonial rule and the potential need for an educated workforce influenced Ghana's higher education mission. To this end, UG established a presence outside of the capital through a regional learning center model, mainly due to the national push to expand education, at all levels, throughout the region. The UG learning centers were pivotal in the evolution of distance education, which serves as the foundation for online learning. Distance education is now an essential conduit for online learning in UG, serving as a point of broad access from all over Ghana to UG’s educational services.

Meanwhile, Ethiopia’s higher education mission was crafted in the aftermath of a brutal Italian occupation. The AAU was founded with the intention of cultivating a pool of highly skilled state managers, business professionals, and diplomats to safeguard Ethiopia's sovereignty from foreign aggression and protect the ruling elite. This founding mandate centered AAU to

Addis Ababa and was based on highly selective access to higher education rather than broad participation. Despite the expansion of its programs and capacity, AAU remains an institution centered in Addis Ababa, and online learning follows a similar trajectory in terms of limited access due to poor connectivity outside of Addis Ababa.

CHAPTER 7 | Discussion

Introduction

This chapter explores several themes in the study and expands on the quantitative and qualitative findings. A discourse on education in the digital age provides a background for exploring the role of online learning in increasing educational access. The study's findings are discussed in comparison, beginning with the quantitative results, followed by the qualitative findings that contextualize the national setting of Ghana and Ethiopia to situate the evolution of the University of Ghana (UG) and Addis Ababa University (AAU), as well as their unique strengths and challenges in deploying online learning. The implication for practice section is based on issues observed in the study, such as the potential for south-south cooperation, data management, and technology deployment. Recommendations for future research follow, and the chapter concludes with closing thoughts.

Study findings

Online vs. face-to-face instruction

The study sought to determine whether online learning had the potential to improve instructional and enrollment capacity in African HEIs. The study investigated the efficacy of online learning at two African universities: the University of Ghana (UG) in Ghana and Addis Ababa University (AAU) in Ethiopia. The study was designed as a sequential mixed-methods investigation, with quantitative findings informing the qualitative investigation. The quantitative data found online learning had a 9.2 % (p-value 0.045) estimated effect in UG and 20.7 % (p-value <0.001) in AAU. This result suggests online learning had a higher estimated effect than face-to-face training; nonetheless, context helps analyze the results.

As discussed in previous chapters, the study did not use the matching method to compare learning outcomes between UG and AAU. However, a comparison of the process of deploying online learning in UG and AAU is instructive in understanding the different approaches to deploying online learning. While both institutions provide online learning with higher efficacy than in-person instruction, UG has the experience and a set procedure for mounting online learning built on a long-established distance learning program. UG learning centers appear to be an essential resource for online learning, acting not only as a hub for learners but also as a compensatory measure for UG's relatively poor IT deployment. AAU's online learning is siloed, with very little coordination and oversight of online learning course development. However, the instructors delivering online learning have created an informal network engaged in skill building and support in developing courses. Moreover, AAU does not have regional centers, and instruction is focused within Addis Ababa, limiting the reach of its online programs. Yet its technical infrastructure is sophisticated and designed to navigate the country's underdeveloped ICT infrastructure.

Enrollment in online learning at UG takes place through a variety of channels. Students choose the modality for reasons ranging from convenience to mobility, and enrollment includes students who could not meet the eligibility cut-off for campus-based admission (Aalangdong, 2022). Finally, UG online learning is also the unit for the Mature Admission Program, an enrollment pathway designed for students over 25 years of age who have decided to return to school to earn their diplomas or degrees. The general perception of online learning is that it is an option for students who could not gain admission through the competitive process, and instruction is somewhat inferior to face-to-face programs. However, the study's findings contradict that general perception.

The matching process controlled for selection bias and performed matching based on student characteristics, pairing students with similar backgrounds and profiles to determine which modality delivered higher learning outcomes. The direct comparison of online and face-to-face students based on their characteristics, age, gender, level, and marital status, found those enrolled in the online modality had a higher CPGA than those enrolled in face-to-face instruction. Therefore, students who were previously ineligible for regular admission to face-to-face instruction but were enrolled in the online program had a higher CGPA of 9.2%, outperforming students who had a higher CGPA at the time of admission. This finding suggests that online learning is more effective than face-to-face instruction, given the marked improvement in students' learning outcomes.

The process of mounting online learning can partly explain this turnaround. According to interviews with UG personnel, mounting online learning begins with reviewing face-to-face course content for online delivery. The procedure entails distance learning experts guiding instructors through online teaching techniques, rewriting course content, and retooling assessment instruments. DDE hosts an instructor retreat where face-to-face lecture PowerPoint presentations are converted into "PowerNotes," comprehensive study guides are created, and assessment instruments are developed (*Department of Distance Learning*, personal communication, March 2, 2023). While not technically an instructional design method, this process reorients instruction from face-to-face to online and allows lecturers to revisit and make necessary changes to their course content, which may not be the case for their face-to-face instruction courses. According to reports, students enrolled in face-to-face versions of online courses are skipping lectures in favor of content uploaded for online students, which they find more thorough and instructive. Furthermore, because DDE has taken the lead in implementing online courses for UG, there is a level of supervision and monitoring of courses offered in the online modality.

Furthermore, UG's online program was created in a system with established adult/continuing education tradition by gradually integrating technology into a distance learning program that began as correspondence, progressed to a module/tutorial model, and is now a hybrid form of online learning (Aalangdong, 2022). This operational background institutionalizes expertise and infrastructure for distance learning. Historically, students in the distance learning program received weekly face-to-face tutorials at the learning centers to reinforce lectures. In the online iteration, tutorials are delivered virtually by course instructors rather than tutors, eliminating the need for weekend and evening tutorials.

The learning center model is also an invaluable asset for UG online learning as it provides educational services to students outside of Accra and compensates for UG's challenging IT infrastructure. The network of centers serves as a resource and help center for students and a location to access free and stable internet connection for students who lack connectivity and cannot afford to purchase data. Learning centers constantly develop solutions to support student access to online learning materials, especially when the UG technical infrastructure fails. For example, students failing exams due to networking and internet connectivity issues was a recurring challenge, forcing them to retake exams and, in some cases, repeat terms and courses. The distance learning unit devised a solution for creating a continuous assessment system for online classes, which uses a proportional scoring system rather than the traditional high-value final exams.

In AAU, online courses and programs are offered through departments. Although a distance and continuing education office exists, its role appears to be more administrative and broad overall coordination. Online courses are housed and offered through regular departments at the request of instructors. The Continuing Education Office establishes admission criteria and rules and regulations for the administration and implementation of online learning. Admission to online programs offered through distance learning programs is governed by the same criteria as admission to departments offering the course. Since the programs are at the graduate level, eligible applicants must also take and pass an entrance examination and produce an original undergraduate degree. Admission requirements for online courses outside distance learning are the same as for campus-based programs. Therefore, regardless of the mode of instruction, AAU has the same admission requirements for online and face-to-face instruction.

The AAU process for developing online programs appears to be largely ad hoc, with little oversight, and instructors who adopt their courses for online delivery do not receive additional compensation. The Continuing Education Office is responsible for policy coordination and does not provide instructional design or technical assistance. In the absence of a coordinating body for online learning, instructors appear to have established an informal network and support structure through which they exchange experiences, offer training, and share resources to improve instruction. As previously stated, instructors initiate online learning courses; thus, there is no external pressure or incentive for instructors to offer classes. Given the additional work and time required to prepare online courses, an instructor proposing an online course is undertaking an unpaid commitment to ensure the success of their online course. Therefore, the high efficacy of online learning raises the question of whether instructors' initiative and entrepreneurship in mounting online learning is a factor in the higher efficacy of 20.7% for online instruction.

Despite AAU's dispersed online learning landscape, the IT infrastructure and technical capabilities are sophisticated and advanced. There has been considerable investment by the government and the institution in building technical capacity for a digital revolution in administration and instruction. The AAU IT office provides technical support for most online courses offered by units on the main campus, *Sidist Kilo,* and through its department level staff for those on other campuses, including selection and provision of LMS. However, extending the decentralized nature of online learning, various campuses appear to be hosted by departments and centers using their own LMS. Also, several peer-to-peer initiatives offer training in different LMS, pointing to a lack of uniform institutional policy in online learning deployment.

However, it's important to understand the national ICT infrastructure to appreciate the sophistication and considerable investment of AAU's IT technical infrastructure. Ethiopia has the lowest internet penetration rate, which stood at 25% in 2022, posing a challenge for those outside the city to participate in online learning effectively. The rate of individual internet use in Ethiopia fell to 16.7% in 2021 after reaching a high of 24% in 2020. There were only 212,000 fixed broadband subscriptions, there were only 654 secure internet servers in the entire country serving a population of 126 million. Moreover, the number of distinct, publicly-trusted TLS/SSL certificates found in the Netcraft Secure Server Survey was only 5.6 per one million residents (*World Bank DataBank*, 2023).

Impact of historical legacy

Although UG and AAU were founded around the same time, the respective countries' historical and social contexts determined each institution's trajectory. The case study revealed the impact of this context on access and its influence on infrastructure development and the reach of educational programs, including online learning.

The UG and AAU were founded as flagship teaching and research institutions, with the development of their respective nations as a critical component of their mandate. The impending end of colonial rule and the potential need for an educated workforce influenced Ghana's higher education mission. Since the early 1800s, a history of modern education in the colonial church and state service has fostered acceptance of formal education in Ghana. At the time of independence, Ghana had an educational system consisting of primary and secondary institutions, with a strong push for establishing a higher education institution (L. J. Lewis, 1960). To that end, UG "was designed to produce graduates who would eventually replace the expatriates serving in civil and public posts throughout the country." UG's founding mandate was to use education as a vehicle for national development, with broad access and a reach beyond the capital.

In contrast, the aftermath of a brutal Italian occupation shaped Ethiopia's higher education mission. The primary concerns were a lack of skilled workforce in the state apparatus and the preservation of the ruling class (E. Ayalew, 2017). The AAU was established to train highly skilled state managers, business professionals, and diplomats from the ranks of the sons of the ruling class enrolled in the three secondary schools "with a sound academic background in the fields of Arts and Science, leading to further professional studies abroad" (Hapte, 1961). Consequently, AAU, at its founding, was closely associated with the aristocracy with a strong emphasis on statecraft. Therefore, while both institutions were founded to train future leaders and government bureaucrats, there are significant differences in approach, owing mainly to the historical and social challenges faced by the respective nations at the time.

UG was founded in a relatively well-established educational landscape, with centers outside the nation's capital to increase access (Acquah & Budu, 2017; L. J. Lewis, 1960). Education was first introduced in Ghana in the colonial forts along the coast to educate the children of Ghanaian women fathered by European men posted in the country, but it quickly spread beyond the coast with the establishment of mission schools. According to Stratmon (1959), Ghana expanded on the colonial-era educational system, particularly at the primary and secondary levels. For example, out of a slightly over 5 million population, Ghana had 204,262 primary and middle school students in 1950, which increased to 415,107 in 1952 (L. J. Lewis, 1960). Around the time of UG's establishment, Ghana's educational system had "40 government owned or assisted secondary schools…1,030 approved middle schools…3,402 accredited primary schools…eight government-owned technical institutes…thirty teacher training colleges [and] a technical college" (Stratmon, 1959, pp. 395–396). Thus, UG was established in an environment with an adequate pool of candidates from across the country eligible for admission to the newly established higher education institution.

AAU emerged in an educational landscape devastated by a six-year Italian occupation from 1936 to 1942. Before that, the Ethiopian Orthodox Church's monastic education dominated Ethiopia's educational landscape for 1,700 years (Bishaw & Lasser, 2012). The first secular modern school was established in 1908 by Emperor Menelik II to contribute to the "maintenance of Ethiopia's sovereignty" by educating "the sons of the nobility in the prevailing international order, modernizing Ethiopia, and training interpreters for international communication" (Bishaw & Lasser, 2012, pp. 53–54). In 1935, 4,200 students enrolled in the 21 government schools in all of Ethiopia at that time, where "9 (42.9%) were in Addis Ababa, showing that Addis Ababa, as the centre of the activities of the Government, has the lion's share from the very start" (S. Ayalew, 1989, p. 33). The year AAU was founded, there were only 540 schools in the Ethiopian educational system, which were predominantly urban (S. Ayalew, 1989). Therefore, the founding of AAU was in the context of a less-developed educational system heavily influenced by an educational agenda that placed access and curriculum at the service of the crown and state.

The primary distinction between UG and AAU is in access and spatial disparity, which are frequently interconnected. Geographic inequality in education service provision is a perennial challenge for African HEIs. Students from disadvantaged regions and rural areas are commonly excluded from postsecondary education due to limited access beginning in primary school. UG and AAU developed solutions to the issues of educational access and geographic disparity to varying degrees. UG addressed the issue head-on by establishing education outposts in learning centers, whereas AAU concentrated on recruiting high-achieving students for admission nationally.

As previously stated, the founding mandate of UG emphasized the importance of broad access to education to achieve development and growth in Ghana. UG's strategy included establishing a presence through learning centers that served as educational service outlets. This learning center model serves as an educational outpost for most Ghanaian institutions, including the University of Cape Coast and Kwame Nkrumah University of Science and Technology. Initially, UG learning centers were established as Workers College in Accra, Takoradi, and Kumasi in 1962 to offer courses leading to certification (Amedzro, 2005). Soon after, the centers were renamed Centers for Ghanaian Workers and then later UG Learning Centers and expanded to eleven locations throughout Ghana *(see Appendix V).*

Until recently, Ghana's Tertiary Gross Enrollment Ratio[22] was significantly lower than the African average; however, this appears to have changed around the same time that higher education institutions adopted and expanded the learning center model. For example, in 1975, Ghana's tertiary level GER was 0.99%, while Africa's rate was 1.6%; by 1994, there was only a

[22] Gross enrolment ratio. Total enrolment in a specific level of education, regardless of age, expressed as a percentage of the population in the official age group corresponding to this level of education. The GER can exceed 100% because of early or late entry and/or grade repetition. (https://learningportal.iiep.unesco.org/en/glossary/gross-enrolment-ratio-ger)

slight improvement with 1.31%, while Africa's rate had more than doubled to 3.8%. It wasn't until 2011 that Ghana began to outperform the regional rate, with 12.07%t versus 8.2% for Africa and rising to 15.57% versus 9% in 2014. Although more research is needed to determine the model's role in increasing tertiary-level enrollment, the framework connects spatial disparity reduction to increased access to Ghana's most remote areas by bringing education to the student rather than vice versa.

In 2014, the learning centers became a department in the School of Continuing and Distance Education, with a mandate to coordinate and carry out educational activities such as tutorials for distance education students, continuing professional development programs for adults, and non-formal programs for community engagement. To demonstrate the impact of this framework on the enrollment increase at the university, UG enrollment in 1950 was 108 and 682 in 1962, but by 2000 it had reached 11,865. In 2013, UG had 40,760 students in 2013, with 14,808 enrolled through the learning center and city campus (UG, 2014). As a result of these learning centers, UG expanded educational access throughout the country, laying the groundwork for distance education (Atuahene & Owusu-Ansah, 2013; L. J. Lewis, 1960). Today, the UG Learning Centers represent the University's presence in their respective regions and have evolved into an important channel for online learning.

Regional disparities in educational provision at all levels have been a feature of Ethiopia's educational system, which Ayalew (1989) referred to as "an obelisk, small at the top and small at the bottom" (1989, p. 35). The lack of pre-college education in the regions and Ethiopia's highly centralized state bureaucracy contributed to AAU's Addis-centered orientation. Ethiopia's GER was among the lowest in the world in 1971, with GER for the primary level at 15.02% and 33.92% in 1980, with no significant improvement until 2000, when the rate surpassed 50% and eventually reached 99.25% in 2014 (UNESCO, 2023b). However, GER for tertiary education was 0.51% in 1980 and 0.85% in 1990, and it wasn't until 2012, when over 34 universities were established throughout the regions, that the rate increased to 8.14% (UN, 2023). Slow growth in primary and secondary education, particularly outside of the capital, and limited access to higher education contributed to the low enrolment rates, which began to improve as regional universities became available and access improved.

When AAU was founded, it was primarily a male-dominated, limited-access institution tasked with preparing students to continue their education abroad. To illustrate this point, AAU had 75 students in its first year, primarily graduates of Addis Ababa's three government schools and less than 14 instructors, all from abroad (Hapte, 1961). Most graduates were sent abroad to further their education after completing a bachelor's degree at AAU. For instance, AAU in 1961 had 169 graduates, of which 136 were enrolled in graduate programs abroad, with 46 in the US, 9 in the UK, 6 in Canada, 3 in France, two each in India and Sweden, and one each in Belgium and Switzerland (Hapte, 1961). AAU's first post-graduate degree programs were launched in 1979 at the master's level and in 1987 at the PhD level (H. Ahmed, 2006).

Although AAU had colleges and programs outside of Addis Ababa and enrolled students from across the country, the majority of its operations and programs were based in the capital. As a result, AAU had no regional presence, and its adult education program consisted primarily of evening classes. Like Ghana, adult and extension education in Ethiopia predated the founding of AAU. In Ethiopia, the only opportunities for adult training were limited to Addis Ababa through the School of Commerce and various evening programs at AAU. However, adult education at AAU did not include establishing a regional presence and infrastructure to support the delivery of its educational services more broadly throughout the country.

The School of Commerce, now part of AAU, was Ethiopia's first postsecondary training institution, founded in 1943, shortly after the end of the Italian occupation, with the specific goal of "training Ethiopians for occupations in the commercial sector following victory over Fascist Italy and the subsequent expulsion of Italians from the country" (*Addis Ababa University,* 2018). Despite being slightly more accessible than AAU, the School of Commerce was still Addis-centered. Its training focused on business operations such as secretarial studies, accounting, banking, and finance. Beyond Addis Ababa, adult education was primarily the responsibility of the Ministry of Education, which initially mandated AAU to deliver correspondence education in 1967, but was later reversed and housed the program within the ministry in the Education Media Agency (E. Ayalew, 2017; UNECA, 1997).

The education system in Ethiopia has been "criticized for being elitist, academic-oriented, and irrelevant to the world of work and…for being urban- and male-biased" (Bishaw & Lasser, 2012, p. 62). Despite expanding its programs and capacity since its inception, AAU remains an institution centered in Addis Ababa. Online learning follows a similar path in terms of access and disciplinary focus. The emphasis on graduate-level training is the central feature of AAU's online learning, with enrollment primarily of working adults employed in the bureaucratic state apparatus and residing in Addis Ababa. Furthermore, while online learning is intended to reach students wherever they are, the majority of AAU's online programs can only be accessed with relative ease within Addis Ababa and its immediate surroundings. This limited distribution of online line programs is primarily due to a lack of AAU outposts to host programs in regional areas, a remnant of previous policy, and Ethiopia's underdeveloped national ICT infrastructure. As a result, AAU's Addis-focused legacy and underdevelopment of digital technology found outside of Addis Ababa impact the expansion of its online learning programs.

Despite the numerous challenges noted above, UG and AAU have developed online learning programs that outperform their face-to-face counterparts in terms of learning outcomes while also increasing enrollment capacity. This was achieved by tailoring the online learning mounting process to the institutional and national contexts. The challenges of UG's limited institutional digital infrastructure and AAU's national digital infrastructure were met with locally appropriate and relevant workarounds. Interestingly, as a result of this process, UG and AAU have developed complementary strengths in the deployment of online learning. While Ghana has one of Africa's most developed ICT infrastructures, with over 80% internet penetration, Ethiopia has one of the weakest, with only 25% interest penetration (*World Bank DataBank*, 2023). However, AAU's strength in online learning lies in providing the technical requirements and support needed for effective technical deployment of online learning, whereas UG is still grappling with basic networking and access issues. In contrast, UG has developed a process and mechanism to monitor the quality of online courses that, by all accounts, has surpassed face-to-face instruction, while AAU lacks a unit that can bring leadership to the academic process of online course development and deployment, however, that does not seem to have impacted the efficacy of the online learning programs. Despite these challenges, UG and AAU deliver higher learning outcomes in online learning, which has meaningful implications for online learning deployment in Africa.

Implications for practice

Even though online learning can potentially increase admissions and reach a wider number of learners, a deficit viewpoint on online learning in Africa persists. The lack of connectivity to facilitate online learning and the shortage of personnel with relevant experience to develop effective programs have been recurring themes in discussions of online learning in Africa.

However, UG and AAU demonstrate an asset-based strategy for deploying online learning by leveraging strengths and developing solutions unique to their context. The study illustrates the importance of adaptation and indigenization. Despite the breadth of literature on online learning deployment, most studies had limited relevance to Ghana and Ethiopia. Despite their differences, UG and AAU have developed adaptations that foster indigenization within their respective national and institutional contexts applicable to other institutions in the region. The similarities in operation, budget, and structure, UG and AAU have the potential to benefit from each other's experience in a South-South exchange model, which can also be scaled up to assist other HEIs in the region.

South-South Cooperation

The concept of South-South Cooperation (SSC) dates to the 1955 Bandung Conference of African and Asian countries, which also gave birth to the Non-Aligned Movement, consisting of countries that do not have bilateral agreements with the United States or Russia. SSC is "in essence any form of cooperation, though normally it refers to trade and socio-economic policy frame-works between two or more countries or regions that are situated in the Global South" (Polonenko et al., 2019, p. 2). The concept is significant in development where exchanging technical expertise and best practices between countries in the Global South[23] provides an alternative to the normative international development framework of aid donor-aid recipient.

The comparison of UG and AAU highlights each institution's complementary strengths and limitations. While UG has demonstrated strength in managing the academic component of online

[23] In this study, the term "Global South" is defined as "a process or practice through which new modes of knowledge production are created and established modes of reproducing inequalities, "epistemicide" (Sousa Santos 2014)..are unlearned…[it is] an active practice that restructures global networks of power….a liminal space of transition in which a phase of anti-structure enables the re-organization of, social and epistemological power relations, and which creates a new model of social, economic, and political interactions that relies on egalitarian principles" (Sinah Theres Kloß, 2017, p. 8).

learning, AAU has mastered technical deployment. Through exchanging ideas and best practices in their respective fields of expertise, each institution could fortify weaknesses with best practices from institutions with similar contexts. Furthermore, lessons from other institutions in the South facing similar challenges, such as UNIMINUTO - Corporación Universitaria Minuto de Dios, Universidad de Cartegena, and UNAD - Universidad Nacional Abierta y a Distancia in Colombia, can provide valuable best practice that may be more appropriate than those from institutions with higher budgets and more developed ICT infrastructure. Thus, South-South cooperation on proven, cost-effective online learning solutions has the potential to yield significant progress in scaling the modality in areas where access is a challenge.

Data management

Data management is essential for informed decisions, planning, budgeting, policy development, and continuous improvement. African higher HEIs collect a massive amount of data on all aspects of operations and business; however, challenges include a lack of data management infrastructure, limited data skills, and an underdeveloped data collection, security, and storage policy. The data collection process for this study revealed issues with institutional data collection, accessibility, accuracy, and storage at UG and AAU. Data appeared to be collected at multiple levels and units, however, whether there was a single institutional data repository was unclear. Furthermore, from program names to degrees and varying date formats, there is a significant lack of uniformity and consistency in data collection. To improve practice in harnessing data and information for institutional growth and improvement, educational institutions must prioritize automation of data collection, analysis, and reporting. Streamlining and standardizing existing data collection processes, upgrading and centralizing institutional data warehousing, and expanding data access for leadership, faculty, and researchers are all crucial steps in the process.

Digital technology deployment

Given the importance of technology in the teaching and learning process, diverse application of technology deployment is critical in online learning programs. Individual connectivity is only as good as the devices from which it is linked and the network to which it is connected, regardless of the sophistication of the regional or national network. The national network may have 5G capacity, but the 5G connection is unavailable if the device is LTE or 2G and the connection is over the telephone network. There are numerous examples of institutions and organizations developing sophisticated digital learning and working environments to discover their students and employees are unable to access them due to high data costs, poor connectivity, and incompatible equipment.

Incorporating appropriate technology for online learning requires a decision-making matrix that provides a phased review of solution suitability as well as a platform for voicing concerns about relevance and user accessibility. Institutions must be deliberate and innovative in determining which technology best fits the environment and accommodates students' limitations, particularly if broader access is the goal. With technological advancements and personal device advancements, there are numerous options and settings that can mitigate high data costs and unstable internet connection, which are frequently built and developed domestically by tech innovators.

Recommendations for future research

Governments, educators, and researchers are still gathering information and data to guide policy, and additional research into online learning is an invaluable resource. The African online learning landscape has yet to be mapped, defined, and cataloged. A more extensive comparative study involving multiple institutions would provide a representative sample of the various perspectives and experiences, along with information on the different online deployment methods. Second, the lack of an accreditation system and a process for evaluating online learning programs make selecting a high-quality program difficult for students unfamiliar with the field. As a result, research into the methods and practices that would inform accreditation would benefit the field.

The processes and technologies used in the deployment of online learning across Africa remain unexplored. The definition, implementation, and goal of online learning differ from one institution to the next, even within the same country. Research into the technological capabilities of multiple institutions' online learning programs and the relationship between academic and technological units will provide insight into best practices and challenges in the field. Furthermore, the instructional design aspect of online learning remains unexplored. A more thorough examination of the role of instructional design in learning outcomes and the deployment of these critical resources in institutions would be instructive for practice. Finally, considering faculty resistance to participating in online learning programs, a deeper dive into faculty attitudes and concerns would begin to offer a path forward.

Conclusion

The study aimed to investigate the potential of technology-mediated online learning as a possible strategy for increasing access and market-relevant skill training in African higher education. HEIs across Africa face the challenge of increasing capacity while dealing with budgetary constraints and an undersupply of teaching staff. In much of Africa, "university education has taken place within an environment of widespread poverty and in most cases is influenced by unjust and discriminatory racial, ethnic, gender and regional considerations" (Kigotho, 2023). This legacy of externally imposed ideologies and agendas has not only hampered higher education development and derailed the natural evolution of HEIs in relation to local realities. Most importantly, it has impeded human capital development, a crucial source of social and economic growth.

Considering this context, this investigation asked whether online learning has the potential to increase capacity by mitigating low capacity in Ghana and Ethiopia, where expanding higher education access is hindered by physical infrastructure and personnel limitations. A mixed-method research methodology was used to examine the efficiency of online learning in Ghana and Ethiopia, contextualized by a qualitative comparative case study.

The quantitative analysis found online learning had a greater positive effect on learning outcomes than face-to-face instruction in UG and AAU. This result suggests that online learning is an effective instructional modality. It also illustrated the online deployment method could be indigenized to increase the modality's efficacy. While online learning is effective, the size and scope of its efficacy and effectiveness are determined by the institutional capacity and the strategies for deployment. The educational landscape, as well as the historical and social context in which the institutions were founded, directed the growth and evolution of UG and AAU. Therefore, the infrastructure and landscape upon which their online learning capacity was built were determined by these circumstances.

The literature on higher education in Africa, online learning, the demographic dividend, and human capital identified challenges to expanding online learning, but the return on investment is clear, and it provides an opportunity to re-imagine human capital development and educational delivery. There are several opportunities and challenges to consider when reevaluating educational delivery to include online learning. First, with young people under 25 comprising the majority of Africa's population, educational access and digital training are critical for individual well-being and productivity. Second, expanding educational access is essential in an era when basic literacy and numeracy are no longer sufficient for navigating society. Moreover, barriers to expanding access include limited national budgets to address the scarcity of classrooms and educators. Finally, the prevalence of skill employment mismatch leaves jobs unfilled and youth unemployment rising. Online learning has the potential to address these challenges and the fundamental issue of expanding educational access while working around existing constraints.

The rapid pace of digital transformation, combined with the urgency of harnessing the digital and demographic dividend, does not provide a wide window of opportunity to address the physical and human resource deficit to increase educational access and digital skills training. The digitalization and automation of society over the last century were slow and compartmentalized compared to the accelerated pace and broader impact on society in this digital era, where the speed, scope, and implications are vast, and the transformation is systemic. Whereas previous innovation was incremental and offered a pause for late adopters to catch up, the digital transformation of this era is immediate, rendering systems obsolete overnight and marginalizing those unable to keep pace.

To appreciate the speed and depth with which technology is transforming the world, consider how quickly digital innovations open new frontiers, challenge established norms and exacerbating the resource divide. Educators in high resourced institutions are wrestling with the implications of Artificial Intelligence (AI) on teaching and learning, whereas those in low resourced schools are grappling with adequate desks and chairs for students. Consider the breadth and depth of digital innovations transforming daily routines and interactions, such as ride-hailing apps, e-commerce, and mobile banking. Due to the sheer impact of the digital revolution across all aspects of life, simple tasks like paying for groceries and hailing a taxi now require basic digital skills, while a large portion of the world struggles with basic literacy and numeracy.

The digital transformation of society has spilled over into the workplace, causing significant changes and disruption. Initially, the areas with the highest losses relied on industrial production, a sector vulnerable to "productivity-enhancing technologies" (Kindberg-Hanlon, 2021). However, "as automation has replaced labor across the entire economy," workplace transformation is expected to be widespread, resulting in "a job market with strong demand at the high and low ends, but a hollowing out of the middle" (Schwab, 2016). Workplace digitization has consequences for education, redefining not only instructional delivery but also training and certification. Only a few years ago, online learning was widely regarded as a possibility; however, online courses are now regularly used by working professionals to fill knowledge gaps, as corporate training tools, and as alternatives to sitting in classrooms for degree seekers.

Additionally, top employers are rethinking certification and training requirements, moving away from traditional majors and degrees. The digital revolution has also changed what it means to be well-trained, shifting away from a college degree and toward specific skill sets documented by certification, supplemented by soft skills such as problem-solving, emotional and cultural intelligence, and digital skills. For instance, Google recently introduced Career Certification[24] in several areas that have equivalent standing to a four-year degree in the Google hiring process. A college degree is no longer required for employment at several companies, including Bank of

[24] https://grow.google/intl/ssa/

America, Random House, IBM, Intel, and Apple. These are systemic global changes, upending established norms and structures at a rate challenging society, the workplace, and training.

Digital transformation and human capital

The digital transformation is taking place during the "age of human capital," when the most valuable asset a country can have are people with "knowledge, information, ideas, skills, and health" (Becker, 2002, p. 3). It is so named because the digital age requires information and data processing to build on innovations. Hence, human capital is an investment in and preparation of individuals with the skills and capabilities to participate in and contribute to this process. Even though automation alters the nature of work at both the functional and task levels, it also affects the structure, context, and education delivery. Becker notes, "[t]echnology may be the driver of a modern economy…but human capital is certainly the fuel" (Becker, 2002, p. 3). A fundamental tenet of human capital theory is the reciprocal relationship between education and innovation. Skilled individuals drive automation and digitization, and the rise in technological advancement necessitates skilled workers to operate and advance it to the next level. Therefore, nations must continue to invest in human capital to not only increase innovation but also to simply keep up with global digital transformations that have profound local consequences.

However, just as there are meaningful dividends from investing in human capital development, there are also inherent risks in failure to make this investment. Africa is a young continent, with over 70% of its population under 30 (United Nations, 2017). This age structure opens enormous opportunities for the region's demographic dividend and has far-reaching implications for its future stability and population well-being. The region's demographic profile could lead to rapid economic growth and development with the right investments and public policies to improve and expand educational opportunity structures. On the other hand, the inability to provide relevant education and employment opportunities to this rapidly growing population of young people creates a ticking time bomb with serious consequences.

Youth unemployment

Inadequate access to education and relevant skill training leads to increased youth unemployment. Youth unemployment and underemployment harm individual long-term productivity, community health, and national development. Unemployed or underemployed youth experience delayed adulthood and independence, social exclusion and dislocation, and marginalization. Therefore, youth unemployment is a complex social, economic, and political issue that, if not addressed, jeopardizes not only development but also peace and security.

The current education-to-employment mismatch is causing more job losses than previously anticipated. According to the Education Commission (2015), up to 2 billion jobs will likely be lost due to automation over the next decade. If current educational trends continue, only one out of every ten students will have acquired the necessary skills for entry-level employment by 2030. However, this estimate was made before the advent of artificial intelligence and its subsequent applications in education and the workplace. According to a recent Goldman Sachs (2023) report, AI will automate one-fourth of all tasks in all industries, including administrative support (46%), community and social services (33%), and healthcare and arts (26%), potentially resulting in the loss of 300 million jobs over the next decade.

Furthermore, according to the African Development Bank, 3 million new jobs are created each year to accommodate an estimated 10 to 12 million young people entering the labor force, a ratio expected to worsen as the youth population grows (AfDB, 2018). On the continent, young workers' employment prospects are bleak, with "one-third unemployed and discouraged, another third not in their jobs, and only one in six in wage employment." Those who find work do so primarily in the informal sector, which lacks protection, benefits, and safe working conditions. In the absence of entrepreneur support to help youth navigate issues such as access to capital and a complex regulatory environment, productive self-employment paths are generally reserved for those with connections to financial and network resources. Furthermore, the impact on young adults not in employment, education, or training (NEET) is significant since they're not gaining training experience and do not have income because they are unemployed. In most cases, young adults with NEET status, mostly women, remain there indefinitely. These circumstances result in a population of young people who are isolated, marginalized, and vulnerable to high-risk migration, radicalization, and extremism.

Investing in education is thus both a human capital development and a national security strategy. Digital transformation serves as a catalyst for increasing the reach and impact of human capital development activities such as education. Moreover, digital transformation has resulted in substantial economic and social distribution, which extends to education and the workplace. The disruption has resulted in economic diversification, changes to traditional employment models, the creation of new industries, and the expansion of entrepreneurship opportunities.

The future of work is in new technology-driven occupations "that emerge… directly from AI adoption" requiring digital training and having the potential to increase employment and individual productivity (Goldman Sachs, 2023, p. 11). According to various forecasts of skill levels required for social integration and employment, countries unable to increase access to educational services and assist young people develop digital skills face dire consequences with disastrous implications for individuals and the economy.

Africa's future lies in leveraging digital technology to expand educational access via various pathways and modalities centered on long- and short-term training and certification. The use of a digital environment for training will not only increase access but will also provide youth with the fundamental competencies and digital skills they need for a better chance at employment and self-employment opportunities, thereby supporting their well-being while contributing to the nation's productivity. Furthermore, training in a digital environment improves students' technological skills, preparing them for a digital society and workplace. As a result, for nations at risk of falling behind in this age of digital transformation, the interaction of education and digital technology provides a potential mechanism for harnessing digital and demographic dividends to boost economic growth.

APPENDICES

Appendix I – Development indicators

Appendix II – Profile of Study Sites

Appendix III – Population Pyramids

Appendix IV Connectivity map

Appendix V – Campuses and Learning Centers

Appendix VI – UG and AAU quantitative analysis

Appendix VII – Qualitative questions

APPENDIX I

Development indicators

The following indictors were compiled from the World Bank DataBank, the World Development Indicators database.

INDICATORS	2015 GHANA	2015 ETHIOPIA	2020 GHANA	2020 ETHIOPIA
Human capital				
Human capital index (HCI), (scale 0-1)	..	..	0.45	0.38
Human capital index (HCI), female (scale 0-1)	..	..	0.46	0.38
GOVERNMENT				
Stability				
Government Effectiveness: Percentile Rank	45.67%	27.40%	45.67%	30.76%
Rule of Law: Percentile Rank	60.09%	35.57%	52.88%	38.94%
Control of Corruption: Percentile Rank	52.40%	40.38%	51.44%	41.34%
Political Stability and Absence of Violence/ Terrorism: Percentile Rank	44.28%	8.09%	53.30%	5.66%
Proportion of seats held by women/ national parliaments (%)	10.91%	38.76%	13.09%	38.76%
Economy				
GDP (current US$)	$ 49,406,568,432.00	$ 64,589,334,978.00	$ 70,043,199,813.00	$ 107,657,734,392.00
GDP growth (annual %)	2.12%	10.39%	0.51%	6.05%
GDP per capita (constant 2015 US$)	$ 1,711.29	$ 630.31	$ 1,951.09	$ 811.26
Adjusted net national income per capita (current US$)	$ 1,350.70	$ 484.61	$ 1,835.40	$ 790.94
GDP per person employed (constant 2017 PPP $)	$ 11,700.37	$ 3,860.06	$ 12,816.17	$ 4,934.12
Personal remittances, received (current US$)	$ 4,982,442,361.79	$ 1,086,986,751.25	$ 4,291,956,800.56	$ 404,088,319.89
GDP per capita growth (annual %)	-0.26%	7.45%	-1.54%	3.28%
Inflation, consumer prices (annual %)	17.14%	9.56%	9.88%	20.35%
Gross national expenditure (% of GDP)	108.85%	120.92%	97.07%	109.75%
National Accounts				
Tax revenue (% of GDP)	11.69%	8.35%	11.34%	6.19%
Personal remittances, received (% of GDP)	10.08%	1.68%	6.12%	0.37%
Mineral rents (% of GDP)	2.35%	0.11%	2.23%	0.08%

Oil rents (% of GDP)	1.29%	0	2.25%	0
Foreign direct investment, net inflows (% of GDP)	6.46%	4.07%	2.67%	2.22%
Foreign direct investment, net outflows (% of GDP)	0.45%	..	0.77%	..
Debt				
Central government debt, total (% of GDP)	..	0.28	..	..
Total debt service (% of GNI)	2.19%	1.71%	3.87%	1.865910831
Debt service on external debt, public and publicly guaranteed (PPG) (TDS, current US$)	$ 926,137,891.00	$ 1,058,933,959.50	$ 2,555,925,023.10	$ 1,970,070,782.60
Multilateral debt service (TDS, current US$)	$ 80,736,400.30	$ 100,822,448.6	$ 170,268,381.30	$ 228,522,949.90
Debt service on external debt, total (TDS, current US$)	$ 1,054,144,096.50	$ 1,102,321,466.40	$ 2,744,754,256.20	$ 1,997,366,859.30
Aid				
Net bilateral aid flows from DAC donors, United Kingdom (current US$)	$ 92,629,997.25	$ 517,619,995.12	$ 44,180,000.31	$ 325,619,995.12
Net bilateral aid flows from DAC donors, United States (current US$)	$ 184,979,995.73	$ 746,429,992.68	$ 205,509,994.51	$ 794,179,992.68
Net official development assistance received (current US$)	$ 1,770,479,980.47	$ 3,238,889,892.58	$ 2,204,219,970.70	$ 5,304,729,980.47
Net official aid received (current US$)	..	..	..	..
Trade				
Trade (% of GDP)	76.52%	39.65%	38.51%	24.00%
Manufactures exports (% of merchandise exports)	8.57%	13.30%	..	13.01%
High-technology exports (% of manufactured exports)	7.57%	6.19%	..	13.09%
ICT goods exports (% of total goods exports)	0.22%	0.53%	..	1.25%
ICT goods imports (% total goods imports)	2.24%	7.49%	..	3.64%
ICT service exports (% of service exports, BoP)	..	3.13%	1.601678147	2.92%
ICT service exports (BoP, current US$)	..	$ 96,758,828.57	$ 121,816,372.91	$ 130,485,959.47
POPULATION				
Population count				
Population, total	28,870,939.00	102,471,895.00	32,180,401.00	117,190,911.00

Population, female (% of total population)	50.13%	49.68%	50.12%	49.73%
Population growth (annual %)	2.36%	2.69%	2.06%	2.65%
Population ages 0-14 (% of total population)	38.85%	42.51%	37.58%	40.31%
Population ages 15-64 (% of total population)	58.00%	54.51%	59.01%	56.55%
Population ages 65 and above (% of total population)	3.13%	2.96%	3.40%	3.13%
Population distribution				
Urban population (% of total population)	54.08%	19.42%	57.34%	21.69%
Urban population growth (annual %)	3.60%	4.93%	3.19%	4.85%
Population in the largest city (% of urban population)	16.75%	19.44%	18.14%	18.85%
Population living in slums (% of urban population)	..	..	33.48%	64.31%
Rural population (% of total population)	45.91%	80.57%	42.65%	78.30%
Rural population growth (annual %)	0.92%	2.16%	0.57%	2.05%
HEALTH				
Expenditures/wellbeing				
Current health expenditure (% of GDP)	4.54%	3.82%	3.99%	3.48%
Current health expenditure per capita (current US$)	$ 77.74	$ 23.53	$ 84.98	$ 28.70
Life expectancy at birth, total (years)	63.175	63.649	64.114	65.371
Life expectancy at birth, female (years)	64.987	66.326	66.385	68.426
Life expectancy at birth, male (years)	61.379	61.126	61.9	62.517
Incidence of malaria (per 1,000 population at risk)	277.09	179.79	165.12	53.052
Incidence of HIV, all (per 1,000 uninfected population)	0.84	0.19	0.69	0.12
Incidence of tuberculosis (per 100,000 people)	160	192	140	129
Physicians (per 1,000 people)	0.1172	..	0.1701	0.1059
Nurses and midwives (per 1,000 people)	2.0017	..	3.6202	0.7844
Hospital beds (per 1,000 people)	..	0.3	..	..
Fertility				
Fertility rate, total (births per woman)	4.05	4.53	3.62	4.24

Adolescent fertility rate (births per 1,000 women ages 15-19)	69.999	76.59	65.152	70.643
Contraceptive prevalence, any method (% of married women ages 15-49)	32.90%	36.90%		37.70%
Contraceptive prevalence, any modern method (% of married women ages 15-49)	28.20%	36%		35.60%
Nutrition				
Prevalence of undernourishment (% of population)	7.70%	14.80%	4.10%	24.90%
Prevalence of moderate or severe food insecurity in the population (%)	38.30%	56.20%	36.60%	56.20%
Prevalence of severe food insecurity in the population (%)	5.10%	14.50%	5.60%	19.60%
Prevalence of stunting, height for age (modeled estimate, % of children under 5)	18.90%	40.10%	14.20%	35.30%
Population access to technology				
Access to electricity (% of population)	74.07%	29%	85.87%	51.09%
Access to electricity, rural (% of rural population)	57.59%	15.49%	73.99%	39.41%
Access to electricity, urban (% of urban population)	88.07%	85%	94.71%	93.24%
Individuals using the Internet (% of population)	23%	13.85%	56.68%	16.42%
Secure Internet servers	200	33	1846	654
Secure Internet servers (per 1 million people)	6.93	0.32	57.36	5.58
Fixed broadband subscriptions	73,132	478,000	78,371	212,000
Fixed broadband subscriptions (per 100 people)	0.25	0.47	0.24	0.18
Fixed telephone subscriptions	275,570	890,642	307,668	1,000,000
Fixed telephone subscriptions (per 100 people)	0.95	0.87	0.96	0.85
Mobile cellular subscriptions	35,008,387	42,311,629	40,461,609	44,500,000
Mobile cellular subscriptions (per 100 people)	121.26	41.29	125.73	37.97
EDUCATION				
Government Spending				
Government expenditure on education, total (% of government expenditure)	23.80%	27.09%	..	..
Government expenditure per student, primary (% of GDP per capita)	..	7.87%	..	..

Government expenditure per student, secondary (% of GDP per capita)	..	16.76%	..	..
Government expenditure per student, tertiary (% of GDP per capita)	..	..	..	..
Expenditure on primary education (% of government expenditure on education)	..	27.45%	..	..
Expenditure on secondary education (% of government expenditure on education)	..	18.13%	..	..
Expenditure on tertiary education (% of government expenditure on education)	..	47.85%	..	..
Enrollment				
School enrollment, preprimary (% gross)	120.86%	29.43%	116.13%	33.25%
School enrollment, preprimary, female (% gross)	122.40%	28.64%	117.20%	32.29%
School enrollment, primary (% gross)	108.33%	100.97%	103.44%	91.90%
School enrollment, primary, female (% gross)	108.31%	96.08%	104.36%	87.13%
School enrollment, secondary (% gross)	67.90%	34.93%	77.67%	..
School enrollment, secondary, female (% gross)	66.10%	34.24%	77.83%	..
School enrollment, secondary, private (% of total secondary)	17.18%	6.62%	15.49%	..
Secondary education, vocational pupils	43,248.00	..	352,134.00	..
Secondary education, vocational pupils (% female)	24.72%		52.33%	..
School enrollment, tertiary (% gross)	15.69%	9.58%	18.68%	..
School enrollment, tertiary, female (% gross)	12.85%	6.80%	17.71%	..
Completion rates				
Primary completion rate, total (% of relevant age group)	0.98%	54.11%	..	68.08%
Primary completion rate, female (% of relevant age group)	98.38%	52.99%	..	65.37%
Lower secondary completion rate, total (% of relevant age group)	74.09%	29.46%	..	..
Lower secondary completion rate, female (% of relevant age group)	71.90%	28.92%	..	..
Female teaching staff				

Primary education, teachers (% female)	38.89%	..	44.53%	41.11%
Secondary education, teachers (% female)	24.40%	..	26.40%	19.62%
Tertiary education, academic staff (% female)	20.58%	..	23.05%	..
Innovation				
Scientific and technical journal articles	774.04	1,017.58	2,106.28	3,967.54
Patent applications, nonresidents	..	32	8	54
Patent applications, residents	..	18	12	6
Out of school				
Children out of school (% of primary school age)	..	14.37%	5.98%	12.79%
Children out of school, female (% of female primary school age)	..	17.56%	5.07%	16.84%
Share of youth not in education, employment or training, female (% of female youth population)	31.33%	..	..	..
Share of youth not in education, employment or training, total (% of youth population)	25.56%	..	..	..
Share of youth not in education, employment or training, male (% of male youth population)	18.51%	..	..	..
EMPLLOYMENT				
Labor force				
Labor force, total	12,224,092.00	47,702,127.00	13,734,537.00	55,819,516.00
Labor force, female (% of total labor force)	47.53%	46.06%	47.83681459	46.53416916
Labor force participation rate, total (% of total population ages 15+) (modeled ILO estimate)	69.25%	80.98%	68.37%	79.80%
Labor force participation rate, female (% of female population ages 15+) (modeled ILO estimate)	65.06%	74.37%	64.69%	73.95%
Labor force participation rate for ages 15-24, total (%) (modeled ILO estimate)	43.42%	73.28%	41.36%	69.85%
Labor force participation rate for ages 15-24, female (%) (modeled ILO estimate)	40.74%	69.58%	39.18%	66.79%
Self-employed, total (% of total employment) (modeled ILO estimate)	76.37%	87.10%	75.71%	86.13%

Self-employed, female (% of female employment) (modeled ILO estimate)	83.98%	90.22%	82.71%	89.69%
Wage and salaried workers, total (% of total employment) (modeled ILO estimate)	23.62%	12.89%	24.28%	13.86%
Wage and salaried workers, female (% of female employment) (modeled ILO estimate)	16.02%	9.77%	17.28%	10.30%
Sectors				
Employment in agriculture (% of total employment) (modeled ILO estimate)	35.17%	68.30%	39.99%	64.08%
Employment in industry (% of total employment) (modeled ILO estimate)	18.68%	8.86%	18.70%	9.91%
Employment in services (% of total employment) (modeled ILO estimate)	46.13%	22.83%	41.29%	26.00%
Unemployment				
Vulnerable employment, total (% of total employment) (modeled ILO estimate)	70.76%	86.62%	70.53%	85.65%
Vulnerable employment, female (% of female employment) (modeled ILO estimate)	79.70%	90.09%	78.79%	89.58%
Unemployment, total (% of total labor force) (modeled ILO estimate)	6.81%	2.57%	3.77%	4.12%
Unemployment, female (% of female labor force) (modeled ILO estimate)	6.58%	3.39%	3.83%	5.27%
Unemployment, youth total (% of total labor force ages 15-24) (modeled ILO estimate)	14.28%	4.01%	7.34%	6.64%
Unemployment, youth female (% of female labor force ages 15-24) (modeled ILO estimate)	13.70%	5.22%	7.34%	8.64%

Data from database: World Development Indicators
Last Updated: 05/10/2023

APPENDIX II

Profile of study sites

University of Ghana
Established 1948

STUDENTS			
	Total student enrollment	**60,396**	
	Undergraduate	53,043	
	Male	*27,543*	*51.30%*
	Female	*26,100*	*48.70%*
	Graduate	7,353	
	Male	*3,869*	*52.60%*
	Female	*3,484*	*47.40%*
	Bachelors	44,474	82.90%
	Masters	6,339	11.80%
	Sub-Degree	1,551	2.90%
	Visiting students	265	0.50%
PERSONNEL			
	Teaching and research staff	**1,248**	
	Male	*882*	
	Female	*366*	
	Administrative staff	243	
	Male	*135*	
	Female	*108*	
TEACHING STAFF			
	Total teaching staff	**1,248**	
	Professor	78	6.30%
	Male	*69*	*7.80%*
	Female	*9*	*2.50%*
	Associate Professor	140	11.20%
	Male	*107*	*12.20%*
	Female	*33*	*9%*
	Senior Lecturer	401	32.1%
	Male	*302*	*34.20%*
	Female	*99*	*27%*
	Lecturer	476	38%
	Male	*308*	*35%*
	Female	*168*	*45.9%*
	Assistant Lecturer	153	12.3%
	Male	*96*	*11%*
	Female	*57*	*16%*

ACADEMIC UNITS

COLLEGE OF EDUCATION

School of Information and Communication Studies

School of Education and Leadership
School of Continuing and Distance Education

College of Humanities

School of Business
School of Law
School of Arts
School of Languages
School of Social Sciences
School of Performing Arts
Institute of Statistical, Social and Economic Research
Institute of African Studies
Regional Institute for Population Studies
Maria Sibylla Merian Institute for Advanced Studies in Africa
Centre for Social Policy Studies
Centre for Migration Studies
Centre for Remote Sensing and Geographic Information Systems
Legon Centre for International Affairs and Diplomacy
Centre for Gender Studies and Advocacy
Language Centre
University of Ghana Accra City Campus

College of Basic and Applied Sciences

School of Agriculture
School of Biological Sciences
School of Engineering Sciences
School of Nuclear and Allied Sciences
School of Physical and Mathematical Sciences
School of Veterinary Medicine
Institute for Environment and Sanitation Studies
Institute of Applied Science and Technology
Livestock and Poultry Research Centre
Soil and Irrigation Research Centre
Forest and Horticultural Crops Research Centre
Biotechnology Research Centre
West Africa Centre for Crop Improvement
West African Center for Cell Biology of Infectious Pathogens
Center for Climate Change and Sustainability Studies

College of Health Sciences

Dental School
Medical School
School of Nursing
School of Pharmacy
School of Public Health
School of Biomedical and Allied Health Sciences
Noguchi Memorial Institute for Medical Research
Centre for Tropical, Clinical Pharmacology & Therapeutics
West African Genetic Medicine Centre

Addis Ababa University
Established 1950

STUDENT		
	Total enrollment	**47,610**
	Undergraduate	29,872
	Masters	15,398
	PhD	2340
STAFFING		
	Total staff	**8,709**
	Teaching staff	3,110
	Administrative support	4,346
	Health teaching staff	1,253
PROGRAMS		
	Total programs	**363**
	Undergraduate	70
	Masters	221
	PhD	72

Campuses

AAU campuses

1. Sidist Kilo Campus(Main Campus)

2. Yekatit 12 campus

3. CBE Campus

4. Yared School Campus

5. Amist Kilo Campus

6. Arat Kilo campus

7. Abune Petros Campus

8. Tikur Anbessa Campus

9. Commerce School Campus

10. Lideta Campus

11. Akaki Campus

12. Bishoftu Campus

13. Salale Campus

14. Art School Campus

15. Sefere Selam Campus

ACADEMIC UNITS

COLLEGE OF BUSINESS AND ECONOMICS
School of Commerce
Department of Accounting and Finance
Department of Economics
Department of Management
Department of Public Administration and Development Management

COLLEGE OF DEVELOPMENT STUDIES
Center for Gender Studies
Center for Environmental and Development Studies
Center for Rural Development Studies
Center for Regional and Local Development Studies
Center for Food Security Studies
Center for Population Studies

COLLEGE OF EDUCATION AND BEHAVIORAL STUDIES
School of Psychology
Department of Curriculum and Teachers' Professional Development Studies
Department of Educational Planning and Management
Department of Science and Mathematics Education
Department of Social Sciences and Language Education
Department of Special Needs Education

COLLEGE OF HEALTH SCIENCES
School of Nursing and Midwifery
School of Pharmacy
School of Public Health
School of Medicine

COLLEGE OF HUMANITIES, LANGUAGE STUDIES, JOURNALISM, AND COMMUNICATION
School of Journalism and Communication
Department of Amharic Language, Literature and Folklore
Department of Oromo Language, Literature and Folklore
Department of Tigrigna Language, Literature and Folklore
Department of Foreign Languages and Literatures
Department of Linguistics

COLLEGE OF LAW AND GOVERNANCE STUDIES
School of Law
Center for Human Rights

Center for Federal Studies

College of natural sciences

School of Information Science
School of Earth Sciences
Department of Chemistry, Department
Department of Mathematics
Department of Microbial, Cellular and Molecular Biology
Department of Computer Science
Department of Physics
Department of Plant Biology and Biodiversity Management
Department of Sport Science
Department of Statistics
Department of Zoological Sciences
Institute of Biotechnology
Institute of Geophysics, Space Science and Astronomy
Environmental Science Center
Food Science Center
Materials Science Program
Computational Science Program
Paleoanthropology and Paleoenvironment Program

College of Performing and Visual Arts

Ale School of Fine Arts and Design
Yared School of Music
School of Theatre Arts
The Gebre Kristos Desta Center
Culture Center

College of Social Sciences

School of Social Work
Department of History
Department of Philosophy
Department of Political Science and International Relations
Department of Social Anthropology
Department of Sociology
Department of Geography and Environmental Studies
Center for African and Oriental Studies
Archaeology and Heritage Management Program

College of Veterinary Medicine and Agriculture

Veterinary Teaching Hospital
Department of Animal Production Studies
Department of Biomedical Sciences
Department of Clinical Studies
Department of Veterinary Microbiology, Immunology and Public Health
Department of Parasitology and Pathology
Department of Agriculture

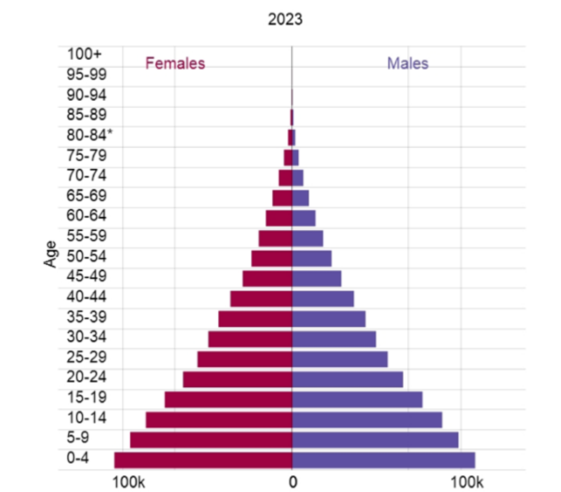
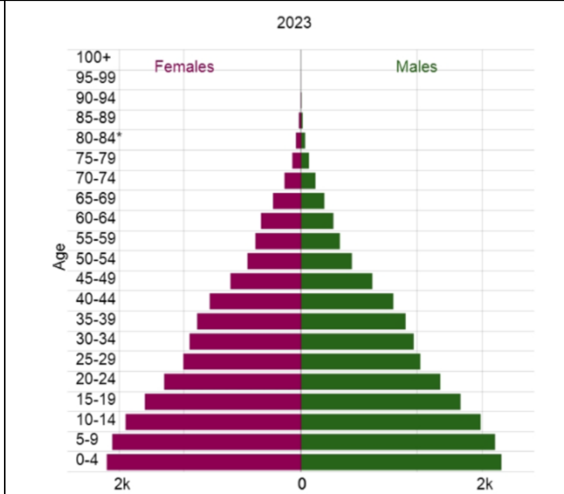
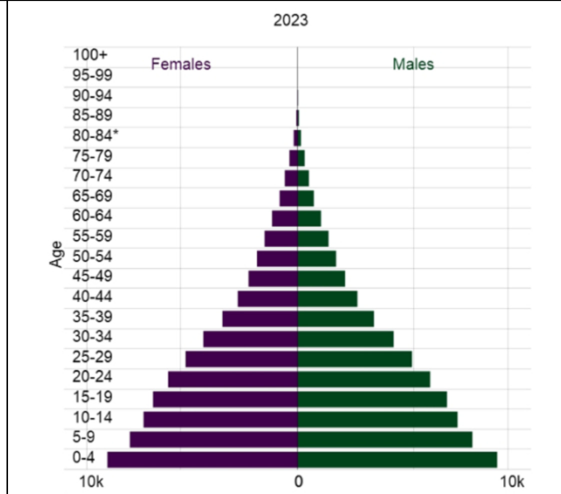
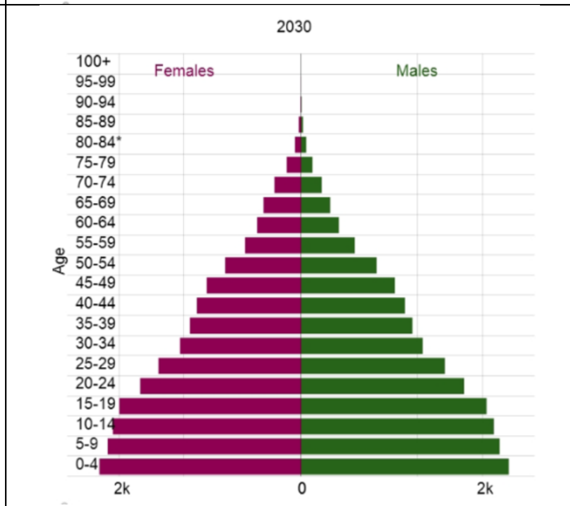
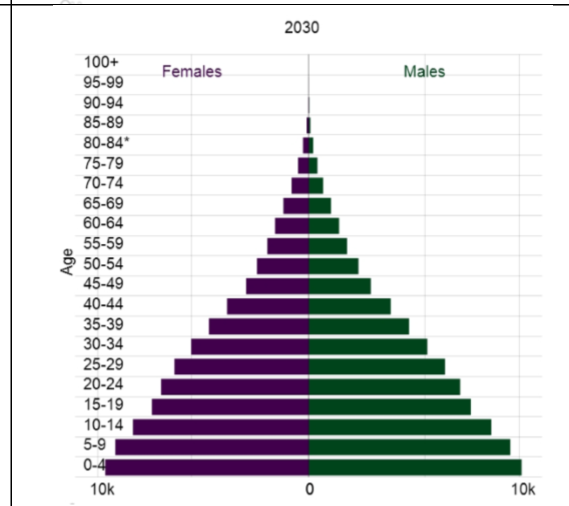
Research and Teaching Institutes

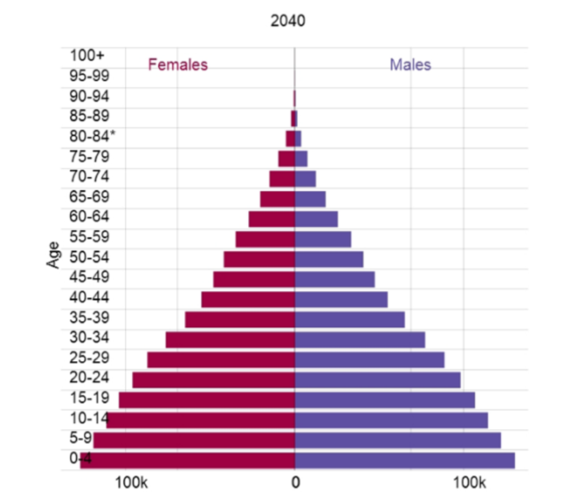
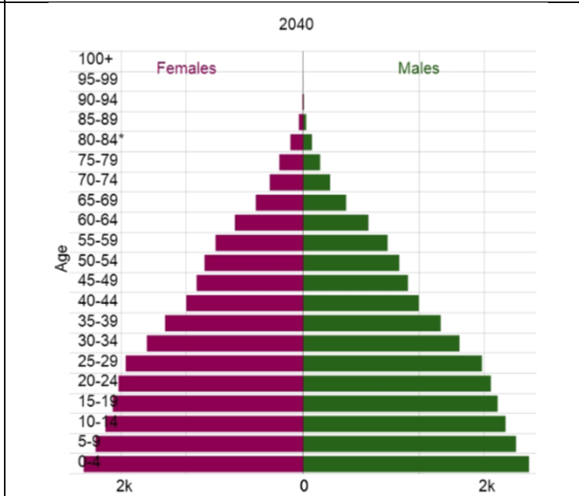
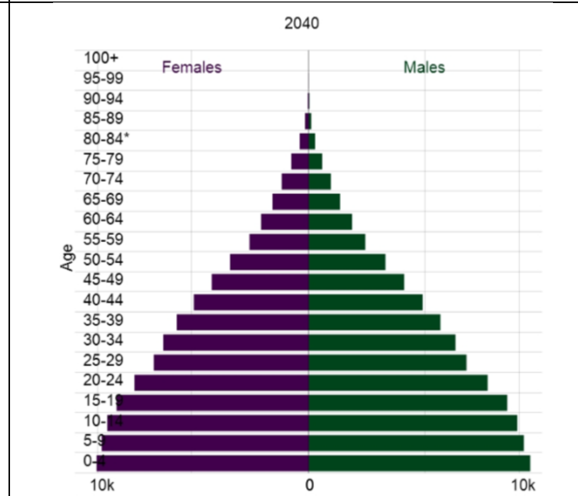
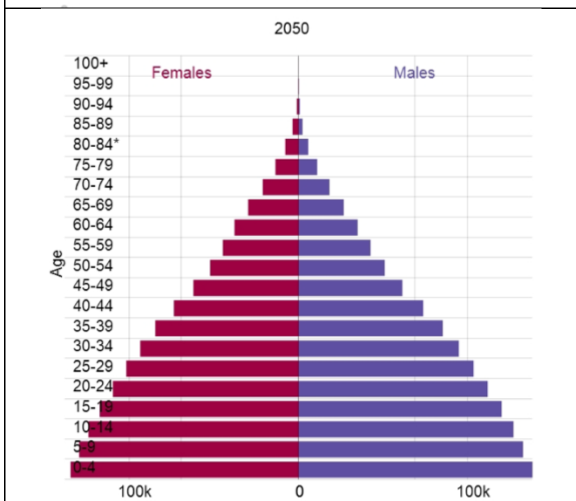
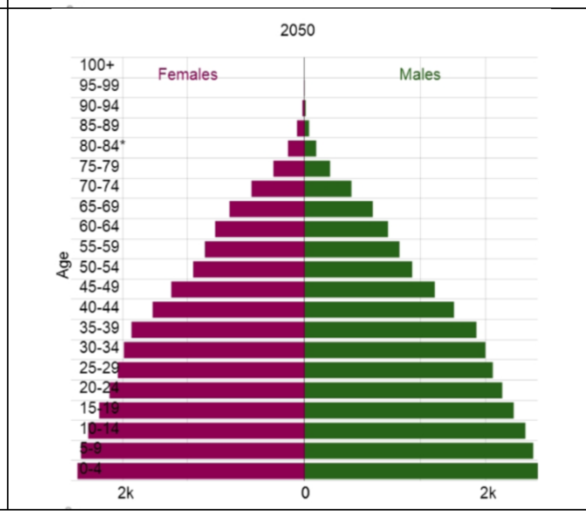
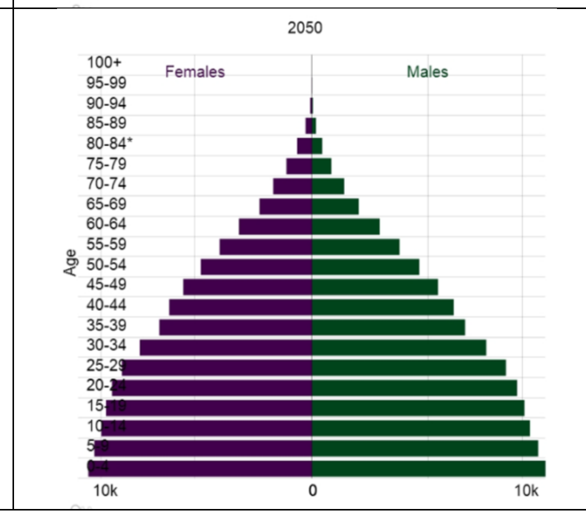
Academy of Ethiopian Languages and Cultures
Addis Ababa Institute of Technology
Aklilu Lemma Institute of Pathobiology
Ethiopian Institute of Architecture, Building Construction and City Development
Ethiopian Institute of Water Resources

Institute of Biotechnology
Institute of Educational Research
Institute of Ethiopian Studies
Institute of Geophysics, Space Science and Astronomy
Institute of Peace and Security Studies
Horn of Africa Regional Center and Environment Network

APPENDIX III

Population Pyramids

AFRICA	GHANA	ETHIOPIA
		
		

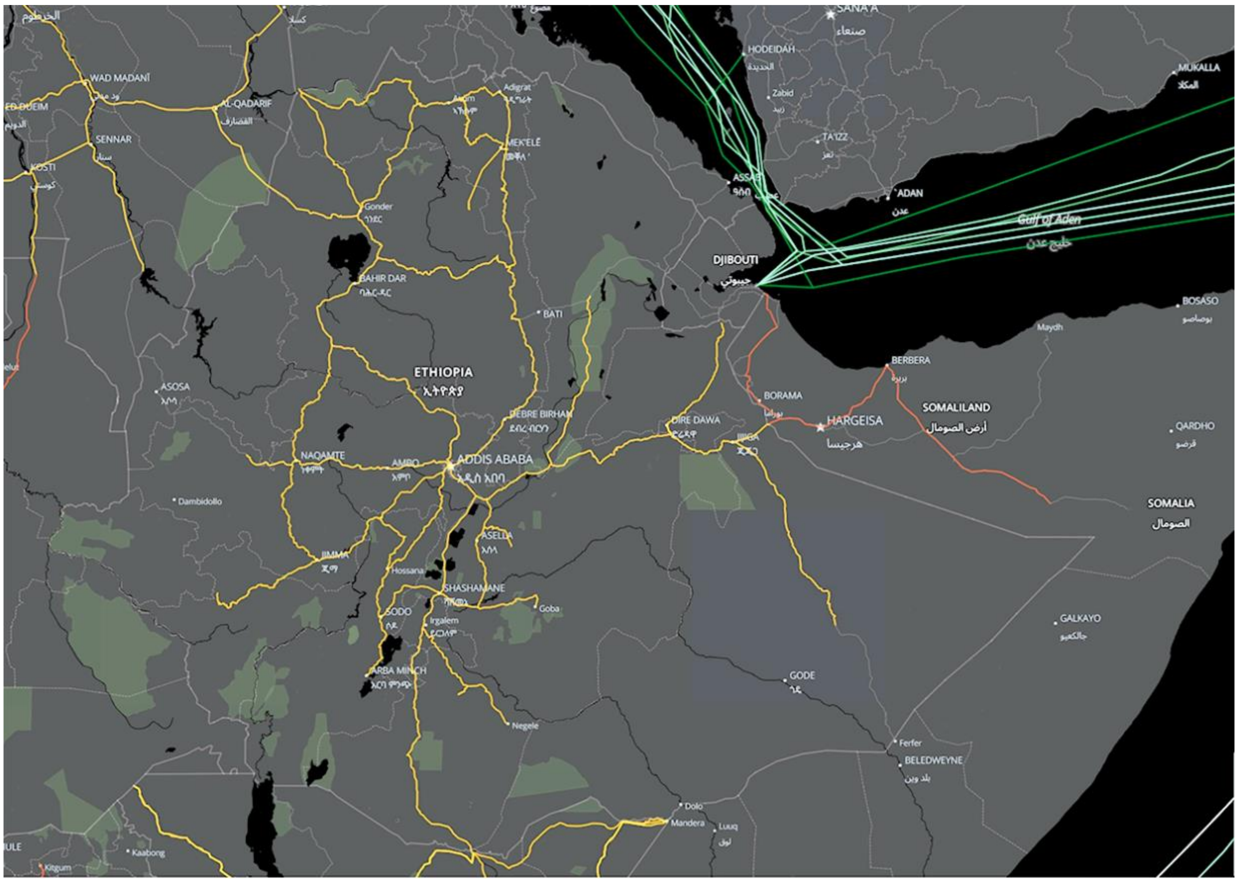
AFRICA	GHANA	ETHIOPIA
		
		

United Nations Department of Economic and Social Affairs Population Division (2022).
Data from "World Population Prospects: The 2022 Revision"
Custom data generated from https://www.un.org/development/dataportal

APPENDIX IV

Connectivity maps

ETHIOPIA



GHANA

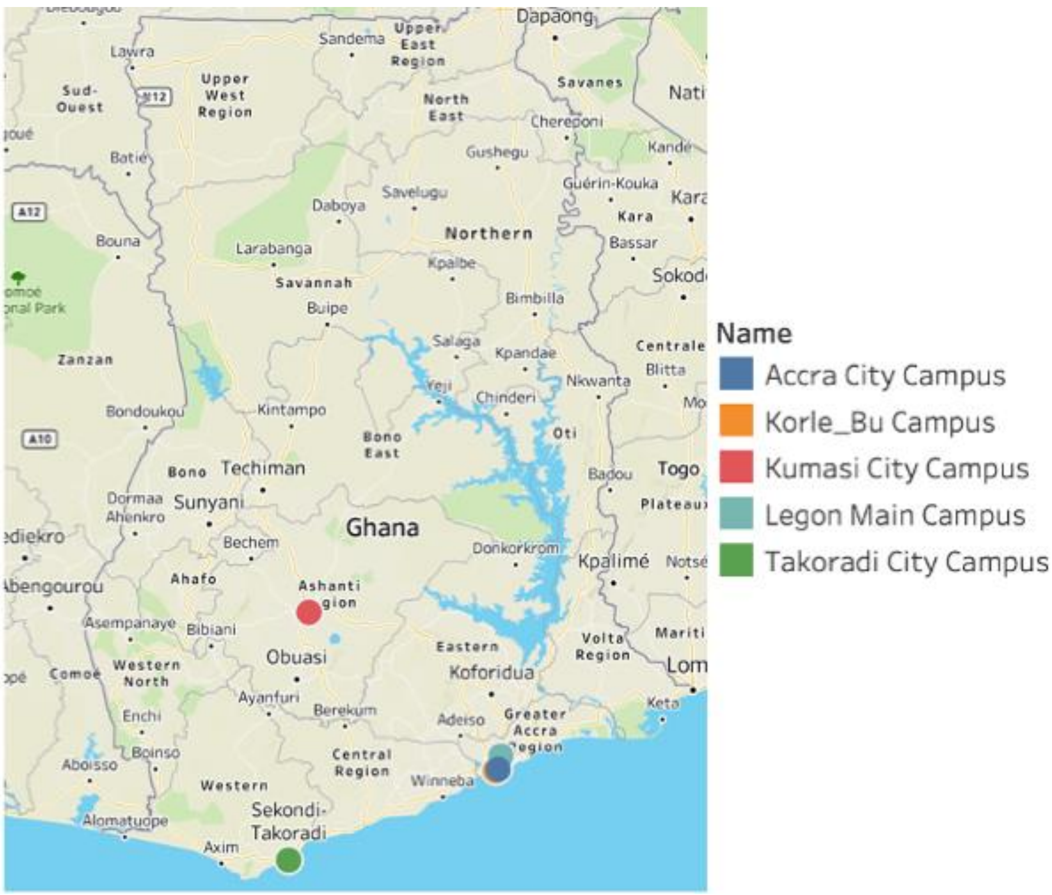
Source: African Undersea and Terrestrial Fibre Optic Cables,
Network Startup Resource Center (NSRC), https://afterfibre.nsrc.org/

APPENDIX V

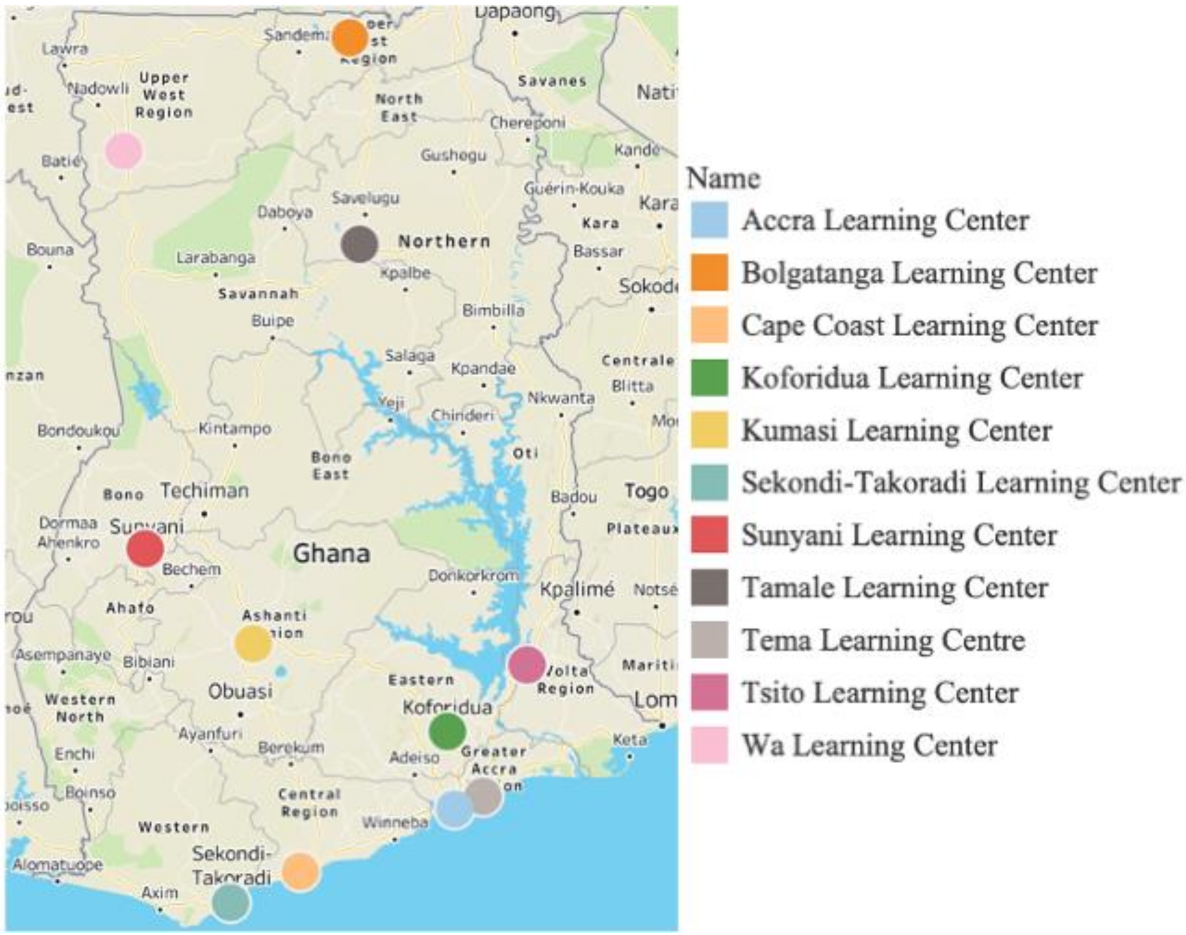
Campuses and learning centers

UNIVERSITY OF GHANA LEARNING CENTERS CAMPUSES

University of Ghana City Campus



University of Ghana Learning Centers

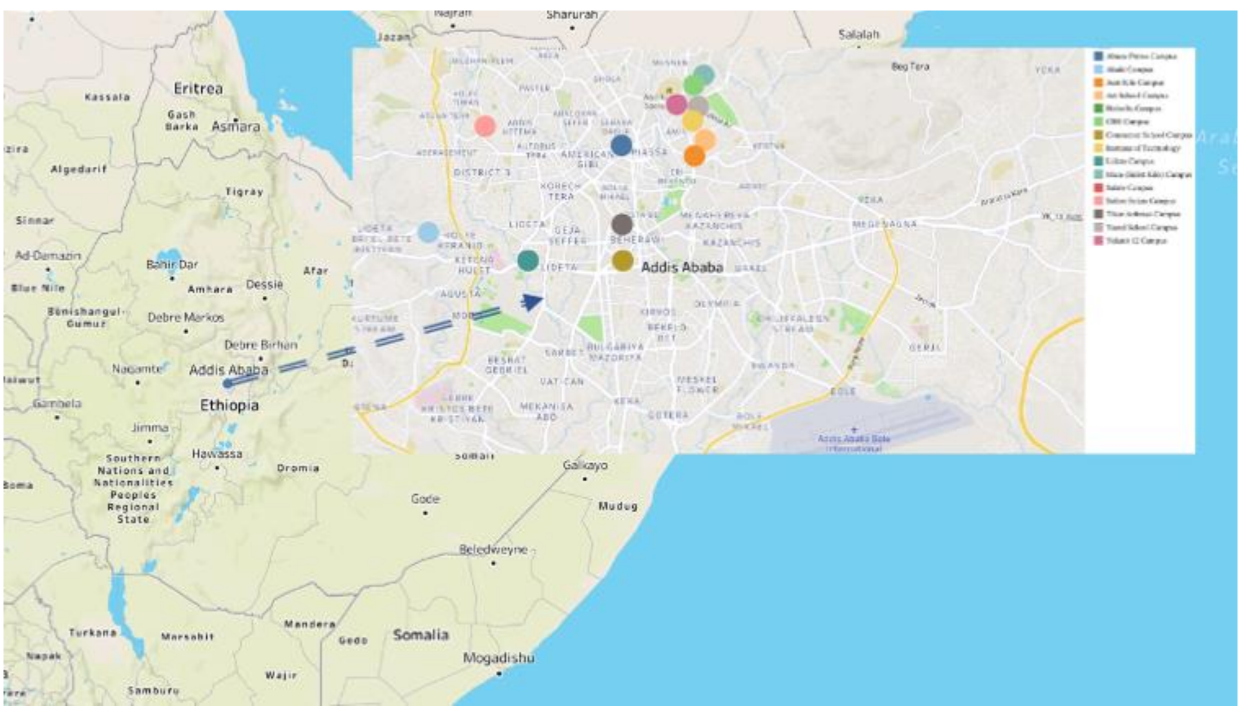


Generated in Tableau from GPS coordinates.

ADDIS ABABA UNIVERSITY CAMPUSES

Addis Ababa University Campuses – All campuses

Addis Ababa University Campuses – Addis Ababa campuses only



Generated in Tableau from GPS coordinates.

APPENDIX VI

Quantitative analysis

University of Ghana and Addis Ababa University

University of Ghana

Descriptive Statistics

Summary

UG Dataset

```r
dfSummary(ug_desc_all,
          plain.ascii  = TRUE,
          style        = "grid",
          graph.magnif = 0.85,
          valid.col    = TRUE)
```

Data Frame Summary
ug_desc_all
Dimensions: 46087 x 11
Duplicates: 0

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
1	uid [numeric]	Mean (sd) : 23044.1 (13304.4) min < med < max: 1 < 23044 < 46092 IQR (CV) : 23043 (0.6)	46087 distinct values	: :	46087 (100.0%)	0 (0.0%)
2	gender [numeric]	Min : 0 Mean : 0.6 Max : 1	0 : 20472 (44.4%) 1 : 25615 (55.6%)	IIIIIIII IIIIIIIIIII	46087 (100.0%)	0 (0.0%)
3	age [numeric]	Mean (sd) : 23 (3.5) min < med < max: 15 < 22 < 60 IQR (CV) : 3 (0.2)	44 distinct values	: : : : . : : .	46087 (100.0%)	0 (0.0%)
4	ms [numeric]	Min : 0 Mean : 1 Max : 1	0 : 190 (0.4%) 1 : 45897 (99.6%)	IIIIIIIIIIIIIIIIIII	46087 (100.0%)	0 (0.0%)

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
5	reg [character]	1. eastern 2. volta 3. ashanti 4. central 5. greater accra 6. brong ahafo 7. western 8. upper west 9. upper east 10. northern [4 others]	10473 (22.7%) 7908 (17.2%) 7547 (16.4%) 6519 (14.1%) 6236 (13.5%) 2139 (4.6%) 1764 (3.8%) 1474 (3.2%) 1267 (2.7%) 691 (1.5%) 69 (0.1%)	IIII III III II II	46087 (100.0%)	0 (0.0%)
6	modality [numeric]	Min : 0 Mean : 0.2 Max : 1	0 : 34918 (75.8%) 1 : 11169 (24.2%)	IIIIIIIIIIIIIII IIII	46087 (100.0%)	0 (0.0%)
7	emp [character]	1. self employed 2. other 3. pensioner/retired 4. artisan/tech/dresser/hair 5. farmer/fisherman 6. univeristy teacher 7. administrative clerk 8. non-commissioned officer 9. lawyer/judge/magistrates 10. military/paramilitary off [22 others]	12597 (27.3%) 6193 (13.4%) 3348 (7.3%) 3047 (6.6%) 2182 (4.7%) 2111 (4.6%) 1808 (3.9%) 1802 (3.9%) 1788 (3.9%) 1766 (3.8%) 9445 (20.5%)	IIIII II I I IIII	46087 (100.0%)	0 (0.0%)
8	cgpa [numeric]	Mean (sd) : 2.5 (0.8) min < med < max: 0 < 2.6 < 4 IQR (CV) : 1.1 (0.3)	391 distinct values	: : : : : . : : : : : . : : : : : : . . . : : : : : : : :	46087 (100.0%)	0 (0.0%)
9	prog [character]	1. BA 2. BS	31036 (67.3%) 15051 (32.7%)	IIIIIIIIIIIII IIIIII	46087 (100.0%)	0 (0.0%)
10	level [numeric]	Mean (sd) : 264 (163.7) min < med < max: 100 < 200 < 800 IQR (CV) : 200 (0.6)	100 : 13122 (28.5%) 200 : 10860 (23.6%) 300 : 10714 (23.2%) 400 : 9112 (19.8%) 800 : 2279 (4.9%)	IIIII IIII IIII III	46087 (100.0%)	0 (0.0%)

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
11	coll [character]	1. basic & applied sciences 2. education 3. health sciences 4. humanities 5. unknown	4519 (9.8%) 6044 (13.1%) 5435 (11.8%) 27507 (59.7%) 2582 (5.6%)	I II II IIIIIIIIIII I	46087 (100.0%)	0 (0.0%)

UG Campus

```r
dfSummary(ug_desc_campus,
          plain.ascii  = TRUE,
          style        = "grid",
          graph.magnif = 0.85,
          valid.col    = TRUE)
```

Data Frame Summary
ug_desc_campus
Dimensions: 34918 x 11
Duplicates: 0

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
1	uid [numeric]	Mean (sd) : 20474.5 (12379) min < med < max: 1 < 20201.5 < 46092 IQR (CV) : 20925.5 (0.6)	34918 distinct values	: . : : : : : : : : : . : : : : : : : : : : : : : : : : : . : : : : : : : : :	34918 (100.0%)	0 (0.0%)
2	gender [numeric]	Min : 0 Mean : 0.5 Max : 1	0 : 16041 (45.9%) 1 : 18877 (54.1%)	IIIIIIIII IIIIIIIIII	34918 (100.0%)	0 (0.0%)
3	age [numeric]	Mean (sd) : 22.3 (2.6) min < med < max: 15 < 22 < 60 IQR (CV) : 2 (0.1)	43 distinct values	: : : : . : :	34918 (100.0%)	0 (0.0%)
4	ms [numeric]	Min : 0 Mean : 1 Max : 1	0 : 109 (0.3%) 1 : 34809 (99.7%)	IIIIIIIIIIIIIIIIIII	34918 (100.0%)	0 (0.0%)
5	reg [character]	1. eastern 2. ashanti 3. volta 4. central 5. greater accra 6. brong ahafo 7. western 8. upper west 9. upper east 10. northern [4 others]	7830 (22.4%) 5835 (16.7%) 5832 (16.7%) 5049 (14.5%) 4804 (13.8%) 1671 (4.8%) 1418 (4.1%) 999 (2.9%) 902 (2.6%) 509 (1.5%) 69 (0.2%)	IIII III III II II	34918 (100.0%)	0 (0.0%)
6	modality [numeric]	1 distinct value	0 : 34918 (100.0%)	IIIIIIIIIIIIIIIIIIII	34918 (100.0%)	0 (0.0%)

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
7	emp [character]	1. self employed 2. other 3. pensioner/retired 4. artisan/tech/dresser/hair 5. non-commissioned officer 6. military/paramilitary off 7. univeristy teacher 8. farmer/fisherman 9. administrative clerk 10. lawyer/judge/magistrates [22 others]	9161 (26.2%) 4581 (13.1%) 2821 (8.1%) 2478 (7.1%) 1524 (4.4%) 1437 (4.1%) 1435 (4.1%) 1358 (3.9%) 1318 (3.8%) 1210 (3.5%) 7595 (21.8%)	IIIII II I I IIII	34918 (100.0%)	0 (0.0%)
8	cgpa [numeric]	Mean (sd) : 2.6 (0.8) min < med < max: 0 < 2.7 < 4 IQR (CV) : 1.1 (0.3)	391 distinct values	. : . : : : . : : : : : : : : : . : . . : : : : : : :	34918 (100.0%)	0 (0.0%)
9	prog [character]	1. BA 2. BS	23093 (66.1%) 11825 (33.9%)	IIIIIIIIIIIII IIIIII	34918 (100.0%)	0 (0.0%)
10	level [numeric]	Mean (sd) : 262.3 (164.7) min < med < max: 100 < 200 < 800 IQR (CV) : 200 (0.6)	100 : 10194 (29.2%) 200 : 8324 (23.8%) 300 : 7844 (22.5%) 400 : 6806 (19.5%) 800 : 1750 (5.0%)	IIIII IIII IIII III I	34918 (100.0%)	0 (0.0%)
11	coll [character]	1. basic & applied sciences 2. education 3. health sciences 4. humanities 5. unknown	4518 (12.9%) 3401 (9.7%) 3559 (10.2%) 21689 (62.1%) 1751 (5.0%)	II I II IIIIIIIIIIII I	34918 (100.0%)	0 (0.0%)

UG Online

```r
dfSummary(ug_desc_online,
          plain.ascii  = TRUE,
          style        = "grid",
          graph.magnif = 0.85,
          valid.col    = TRUE)
```

Data Frame Summary
ug_desc_online
Dimensions: 11169 x 11
Duplicates: 0

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
1	uid [numeric]	Mean (sd) : 31077.3 (12890.1) min < med < max: 10 < 35184 < 46090 IQR (CV) : 21269 (0.4)	11169 distinct values	: : . : : . . . : : . : . : . : : : : :	11169 (100.0%)	0 (0.0%)
2	gender [numeric]	Min : 0 Mean : 0.6 Max : 1	0 : 4431 (39.7%) 1 : 6738 (60.3%)	IIIIIII IIIIIIIIIIII	11169 (100.0%)	0 (0.0%)
3	age [numeric]	Mean (sd) : 25.4 (4.7) min < med < max: 16 < 24 < 57 IQR (CV) : 6 (0.2)	38 distinct values	: : : : : : : : : : : .	11169 (100.0%)	0 (0.0%)
4	ms [numeric]	Min : 0 Mean : 1 Max : 1	0 : 81 (0.7%) 1 : 11088 (99.3%)	IIIIIIIIIIIIIIIIIII	11169 (100.0%)	0 (0.0%)
5	reg [character]	1. ashanti 2. brong ahafo 3. central 4. eastern 5. greater accra 6. northern 7. upper east 8. upper west 9. volta 10. western	1712 (15.3%) 468 (4.2%) 1470 (13.2%) 2643 (23.7%) 1432 (12.8%) 182 (1.6%) 365 (3.3%) 475 (4.3%) 2076 (18.6%) 346 (3.1%)	III II IIII II III	11169 (100.0%)	0 (0.0%)
6	modality [numeric]	1 distinct value	1 : 11169 (100.0%)	IIIIIIIIIIIIIIIIIIII	11169 (100.0%)	0 (0.0%)

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
7	emp [character]	1. self employed 2. other 3. farmer/fisherman 4. univeristy teacher 5. lawyer/judge/magistrates 6. artisan/tech/dresser/hair 7. pensioner/retired 8. administrative clerk 9. military/paramilitary off 10. non-commissioned officer [19 others]	3436 (30.8%) 1612 (14.4%) 824 (7.4%) 676 (6.1%) 578 (5.2%) 569 (5.1%) 527 (4.7%) 490 (4.4%) 329 (2.9%) 278 (2.5%) 1850 (16.6%)	IIIIII II I I I I III	11169 (100.0%)	0 (0.0%)
8	cgpa [numeric]	Mean (sd) : 2.3 (0.7) min < med < max: 0 < 2.3 < 4 IQR (CV) : 1 (0.3)	356 distinct values	: : : : : . . : : : : : : : : : : . : : : : : : : .	11169 (100.0%)	0 (0.0%)
9	prog [character]	1. BA 2. BS	7943 (71.1%) 3226 (28.9%)	IIIIIIIIIIIIII IIIII	11169 (100.0%)	0 (0.0%)
10	level [numeric]	Mean (sd) : 269.2 (160.4) min < med < max: 100 < 300 < 800 IQR (CV) : 300 (0.6)	100 : 2928 (26.2%) 200 : 2536 (22.7%) 300 : 2870 (25.7%) 400 : 2306 (20.6%) 800 : 529 (4.7%)	IIIII IIII IIIII IIII	11169 (100.0%)	0 (0.0%)
11	coll [character]	1. basic & applied sciences 2. education 3. health sciences 4. humanities 5. unknown	1 (0.0%) 2643 (23.7%) 1876 (16.8%) 5818 (52.1%) 831 (7.4%)	IIII III IIIIIIIIII I	11169 (100.0%)	0 (0.0%)

Descriptive statistics

UG Dataset

```
descr(ug_desc_all)
```

```
## Non-numerical variable(s) ignored: reg, emp, prog, coll
```

Descriptive Statistics

ug_desc_all
N: 46087

	age	cgpa	gender	level	modality	ms	uid
Mean	23.03	2.48	0.56	263.99	0.24	1.00	23044.07
Std.Dev	3.53	0.82	0.50	163.67	0.43	0.06	13304.44
Min	15.00	0.00	0.00	100.00	0.00	0.00	1.00
Q1	21.00	2.01	0.00	100.00	0.00	1.00	11522.00
Median	22.00	2.60	1.00	200.00	0.00	1.00	23044.00
Q3	24.00	3.09	1.00	300.00	0.00	1.00	34566.00
Max	60.00	4.00	1.00	800.00	1.00	1.00	46092.00
MAD	2.97	0.80	0.00	148.26	0.00	0.00	17082.52
IQR	3.00	1.08	1.00	200.00	0.00	0.00	23043.00
CV	0.15	0.33	0.89	0.62	1.77	0.06	0.58
Skewness	2.09	-0.82	-0.22	1.55	1.20	-15.48	0.00
SE.Skewness	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Kurtosis	7.46	0.64	-1.95	3.08	-0.55	237.56	-1.20
N.Valid	46087.00	46087.00	46087.00	46087.00	46087.00	46087.00	46087.00
Pct.Valid	100.00	100.00	100.00	100.00	100.00	100.00	100.00

UG Campus

```
descr(ug_desc_campus)
```

```
## Non-numerical variable(s) ignored: reg, emp, prog, coll
```

Descriptive Statistics

ug_desc_campus
N: 34918

	age	cgpa	gender	level	modality	ms	uid
Mean	22.28	2.55	0.54	262.32	0.00	1.00	20474.55
Std.Dev	2.65	0.84	0.50	164.69	0.00	0.06	12378.99
Min	15.00	0.00	0.00	100.00	0.00	0.00	1.00
Q1	21.00	2.10	0.00	100.00	0.00	1.00	9891.00
Median	22.00	2.69	1.00	200.00	0.00	1.00	20201.50
Q3	23.00	3.17	1.00	300.00	0.00	1.00	30817.00
Max	60.00	4.00	1.00	800.00	0.00	1.00	46092.00
MAD	1.48	0.77	0.00	148.26	0.00	0.00	15447.21
IQR	2.00	1.07	1.00	200.00	0.00	0.00	20925.50
CV	0.12	0.33	0.92	0.63	NaN	0.06	0.60
Skewness	2.48	-1.00	-0.16	1.57	NaN	-17.81	0.10
SE.Skewness	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Kurtosis	15.41	0.99	-1.97	3.07	NaN	315.33	-1.13
N.Valid	34918.00	34918.00	34918.00	34918.00	34918.00	34918.00	34918.00
Pct.Valid	100.00	100.00	100.00	100.00	100.00	100.00	100.00

UG Online

```
descr(ug_desc_online)
```

```
## Non-numerical variable(s) ignored: reg, emp, prog, coll
```

Descriptive Statistics

ug_desc_online
N: 11169

	age	cgpa	gender	level	modality	ms	uid
Mean	25.36	2.27	0.60	269.19	1.00	0.99	31077.26
Std.Dev	4.72	0.70	0.49	160.36	0.00	0.08	12890.15
Min	16.00	0.00	0.00	100.00	1.00	0.00	10.00
Q1	22.00	1.80	0.00	100.00	1.00	1.00	21213.00
Median	24.00	2.31	1.00	300.00	1.00	1.00	35184.00
Q3	28.00	2.79	1.00	400.00	1.00	1.00	42482.00
Max	57.00	3.96	1.00	800.00	1.00	1.00	46090.00
MAD	4.45	0.73	0.00	148.26	0.00	0.00	13143.25
IQR	6.00	0.99	1.00	300.00	0.00	0.00	21269.00
CV	0.19	0.31	0.81	0.60	0.00	0.09	0.41
Skewness	1.12	-0.35	-0.42	1.51	NaN	-11.61	-0.65
SE.Skewness	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Kurtosis	1.76	-0.17	-1.82	3.11	NaN	132.87	-0.87
N.Valid	11169.00	11169.00	11169.00	11169.00	11169.00	11169.00	11169.00
Pct.Valid	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Gender

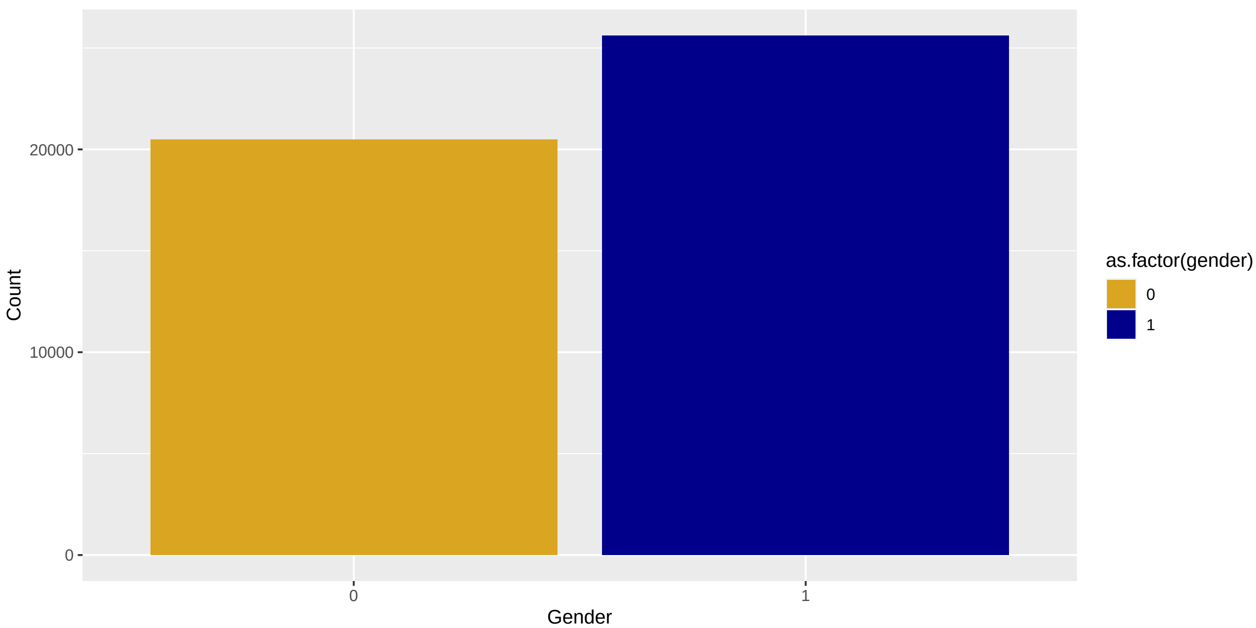
UG Dataset - Frequency

```
freq(ug_desc_all$gender, plain.ascii = TRUE, style = 'grid')
```

Frequencies
ug_desc_all$gender
Type: Numeric

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
0	20472	44.42	44.42	44.42	44.42
1	25615	55.58	100.00	55.58	100.00
<NA>	0			0.00	100.00
Total	46087	100.00	100.00	100.00	100.00

```
ggplot(ug_desc_all, aes(x=as.factor(gender), fill = as.factor(gender))) +
  geom_bar()+ xlab("Gender") + ylab("Count") +
  scale_fill_manual(values = c("goldenrod", "darkblue"))
```



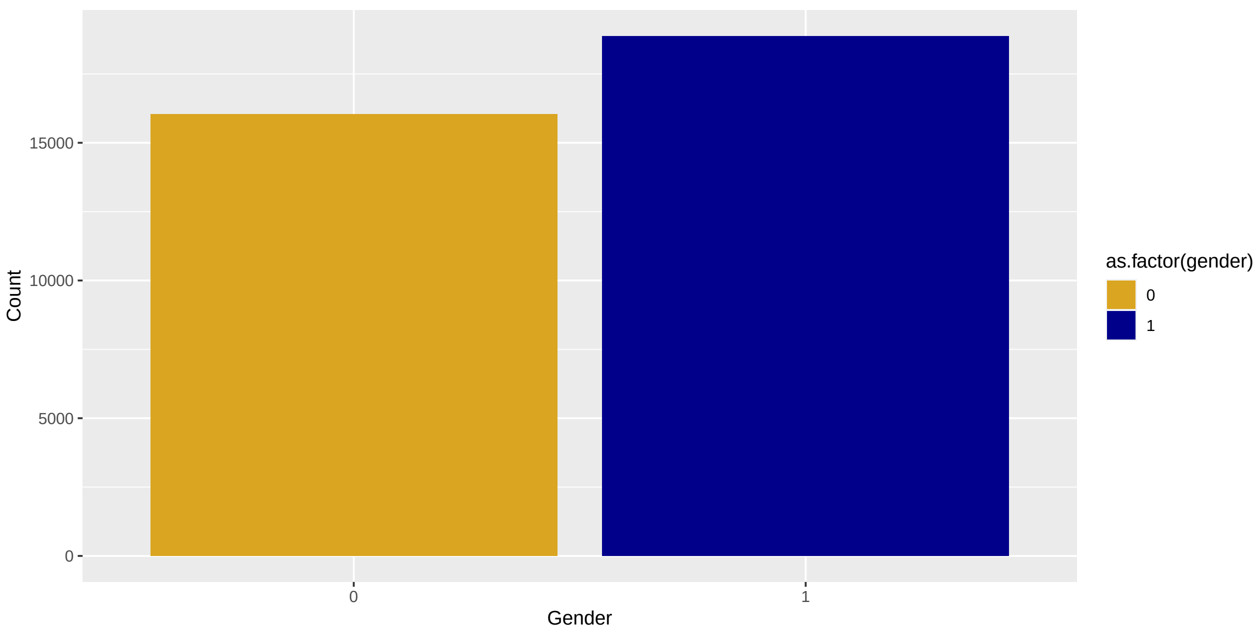
UG Campus- Frequency

```r
freq(ug_desc_campus$gender, plain.ascii = TRUE, style = 'grid')
```

Frequencies
ug_desc_campus$gender
Type: Numeric

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
0	16041	45.94	45.94	45.94	45.94
1	18877	54.06	100.00	54.06	100.00
<NA>	0			0.00	100.00
Total	34918	100.00	100.00	100.00	100.00

```r
ggplot(ug_desc_campus, aes(x=as.factor(gender), fill = as.factor(gender))) +
  geom_bar() + xlab("Gender") + ylab("Count") +
  scale_fill_manual(values = c("goldenrod", "darkblue"))
```



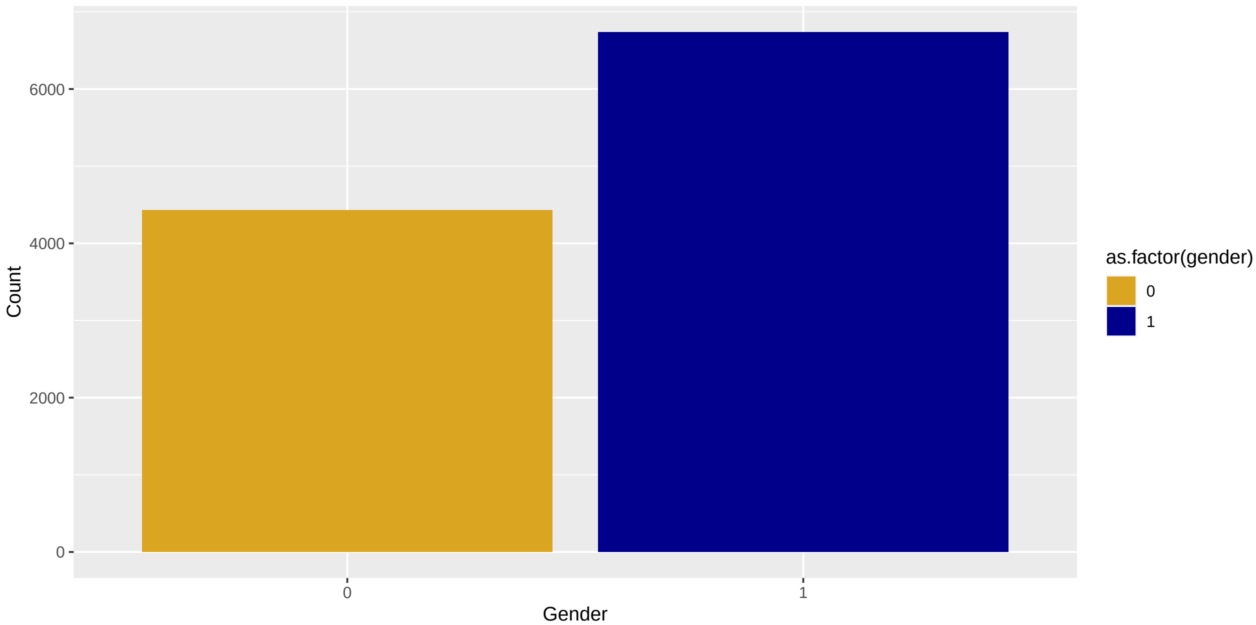
UG Online- Frequency

```r
freq(ug_desc_online$gender, plain.ascii = TRUE, style = 'grid')
```

Frequencies
ug_desc_online$gender
Type: Numeric

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
0	4431	39.67	39.67	39.67	39.67
1	6738	60.33	100.00	60.33	100.00
<NA>	0			0.00	100.00
Total	11169	100.00	100.00	100.00	100.00

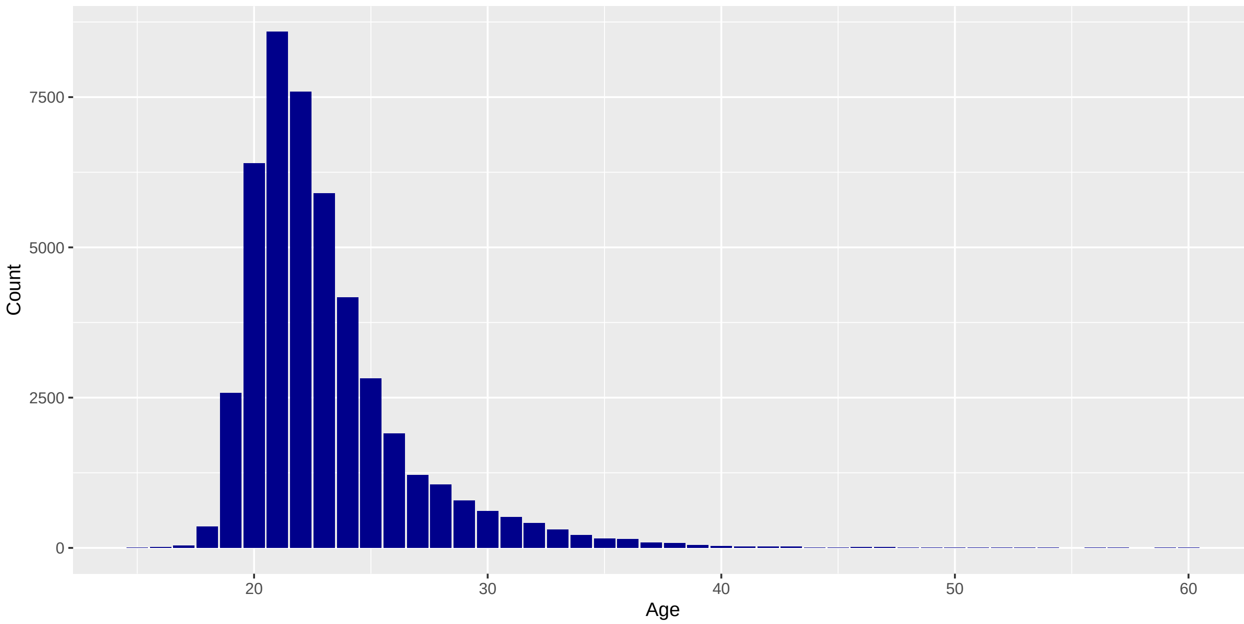
```
ggplot(ug_desc_online, aes(x=as.factor(gender), fill = as.factor(gender))) +
  geom_bar() + xlab("Gender") + ylab("Count") +
  scale_fill_manual(values = c("goldenrod", "darkblue"))
```



Age

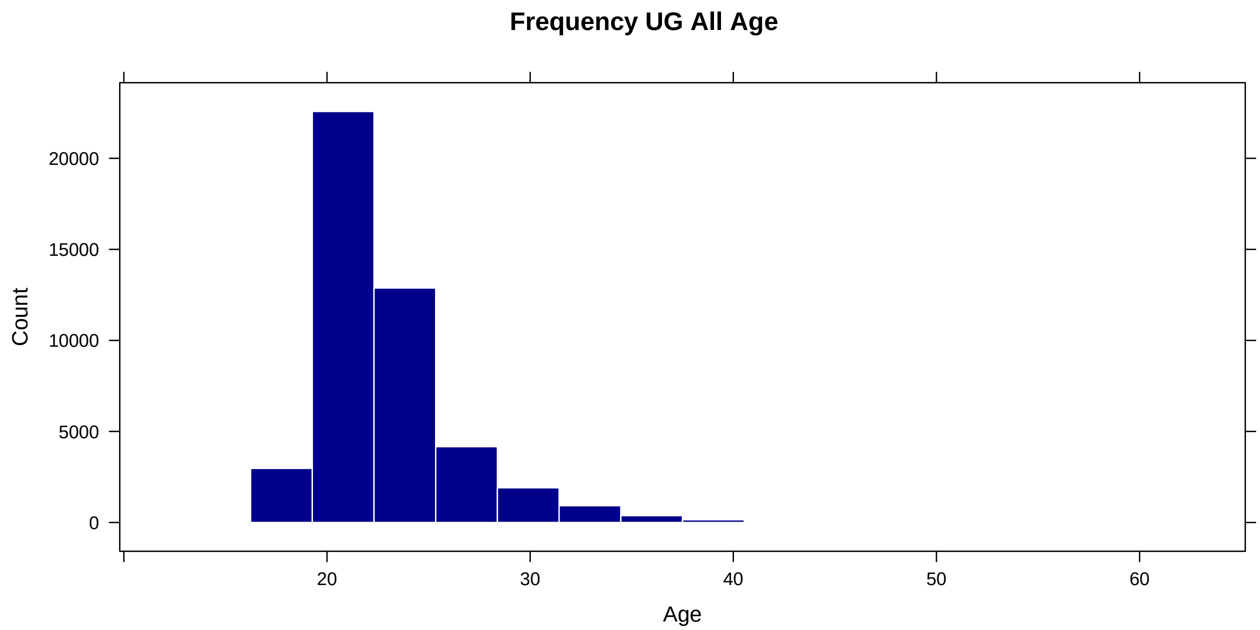
UG Dataset - Frequency

```
ggplot(ug_desc_all, aes(x=age)) +
  geom_bar(fill="darkblue") + xlab("Age") + ylab("Count")
```



UG Dataset - Histogram

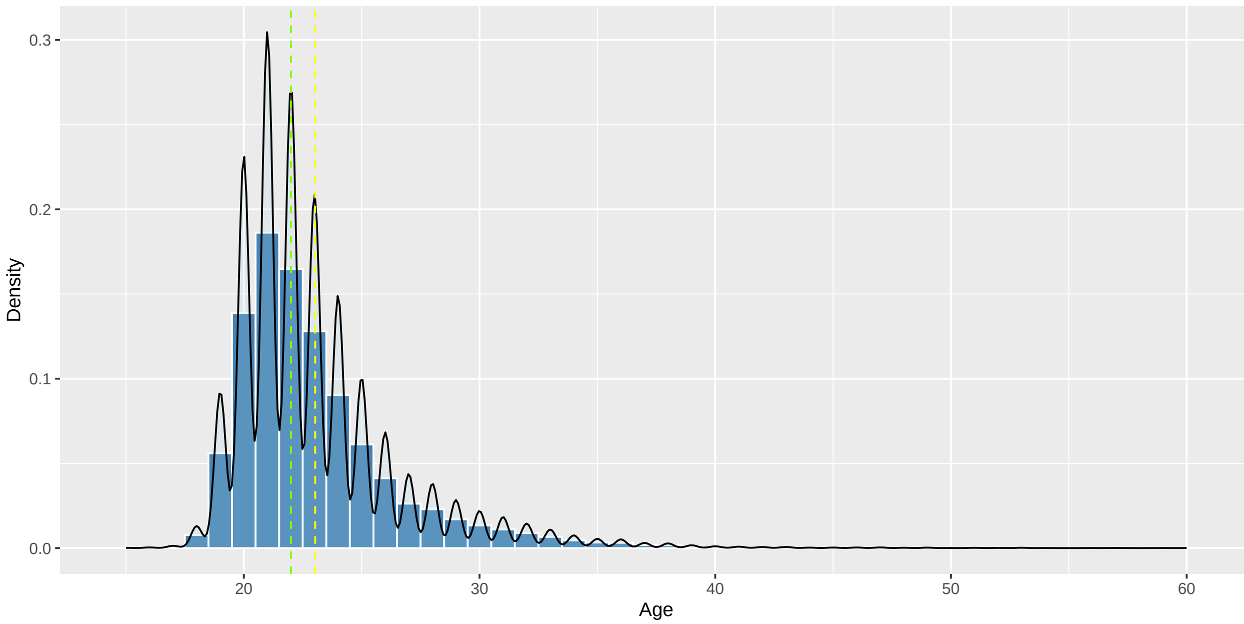
```
histogram(ug_desc_all$age,
          type = "count", main='Frequency UG All Age', xlab='Age',
          col='darkblue', border = "white")
```



UG Dataset - Histogram with Density

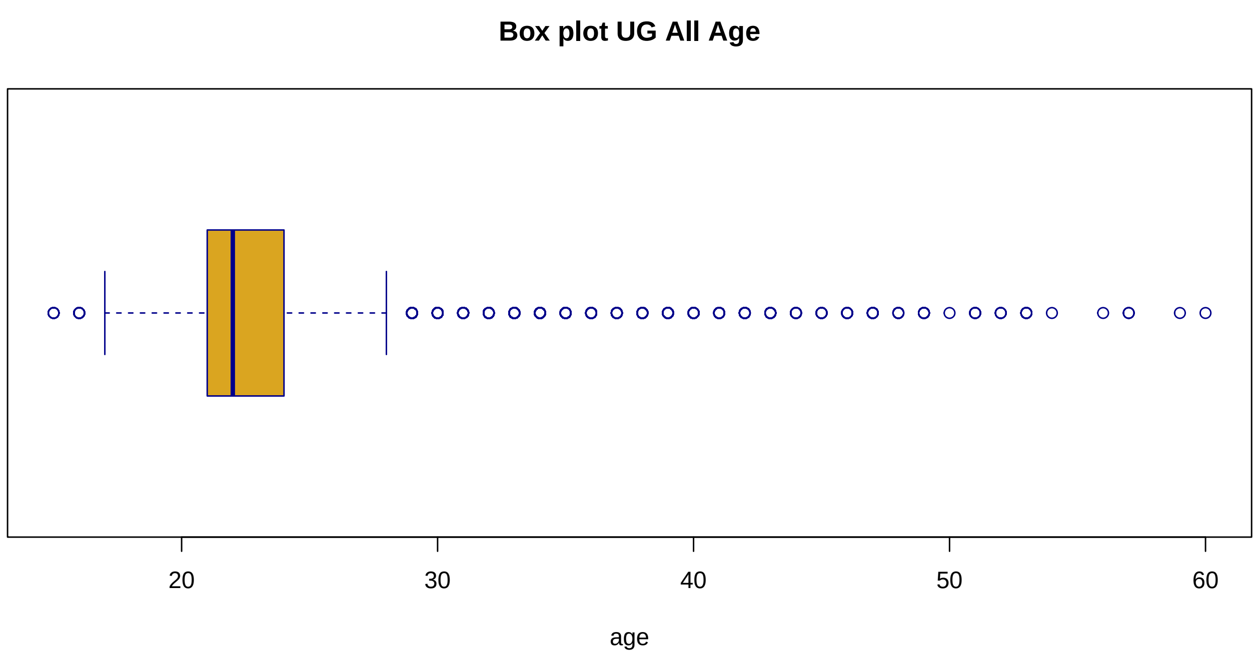
```
ggplot(ug_desc_all, aes(x=age)) +
 geom_histogram(aes(y=..density..),  binwidth= 1, colour="white", fill="steelblue") +
 geom_density(alpha=.2, fill="lightblue") +
geom_vline(aes(xintercept=mean(age)),color="yellow", linetype="dashed") +
  geom_vline(aes(xintercept=median(age)), color="chartreuse", linetype="dashed") +
  labs(x="Age", y="Density")
```

```
## Warning: The dot-dot notation (`..density..`) was deprecated in ggplot2 3.4.0.
## i Please use `after_stat(density)` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```



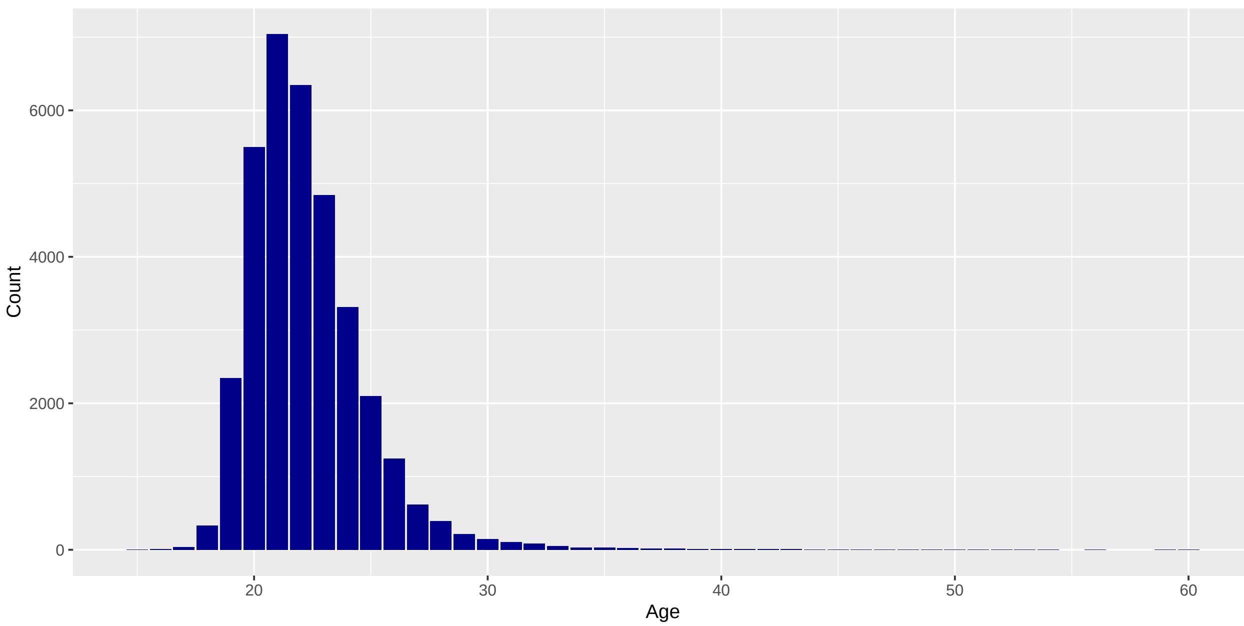
UG Dataset - Box plot

```
boxplot(ug_desc_all$age,
main = "Box plot UG All Age", xlab = "age", col = "goldenrod", border = "darkblue",
horizontal = TRUE, notch = FALSE)
```



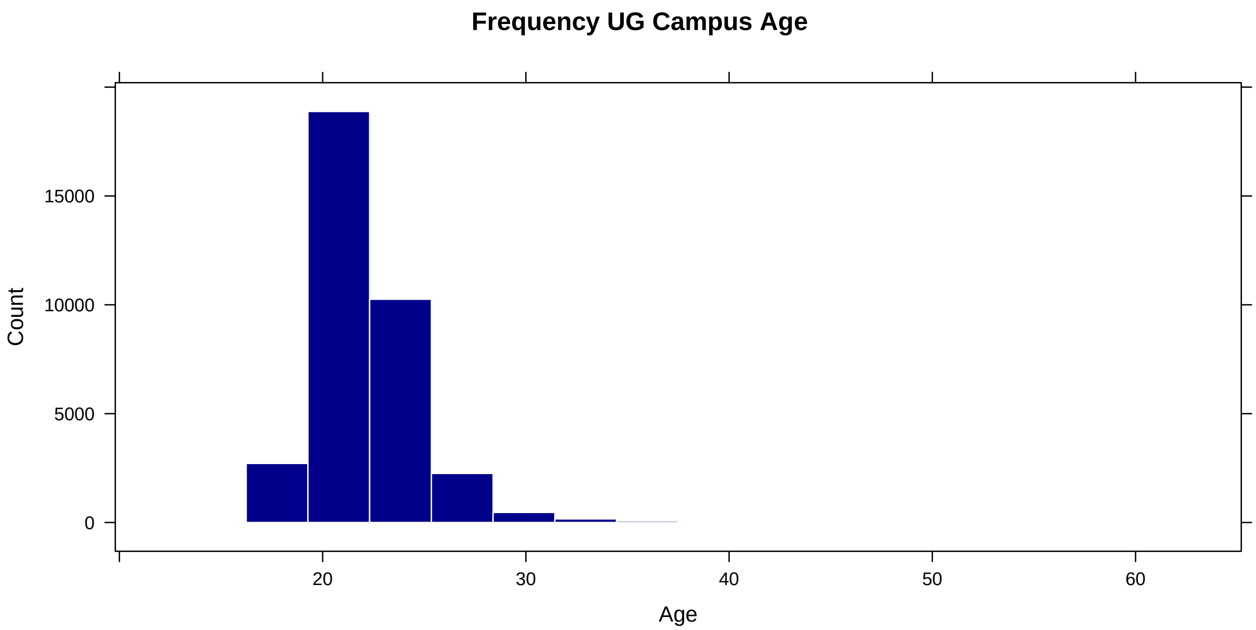
UG Campus - Frequency

```
ggplot(ug_desc_campus, aes(age)) + xlab("Age") + ylab("Count") +
  geom_bar(fill = "darkblue")
```



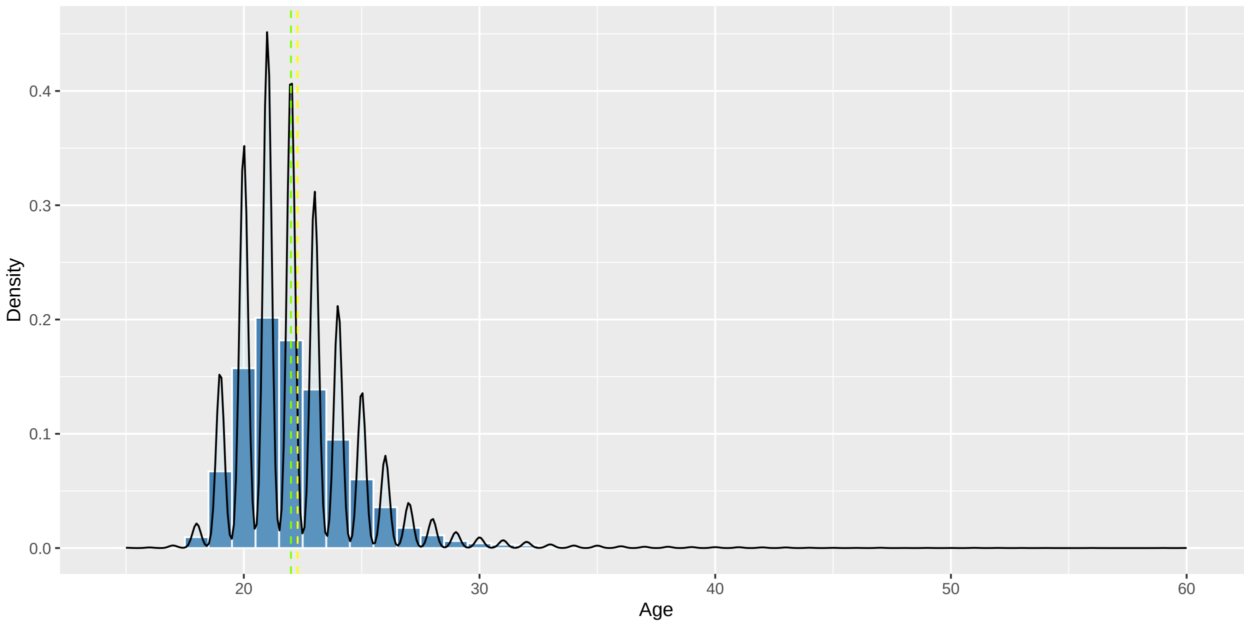
UG Campus - Histogram

```
histogram(ug_desc_campus$age,
          type = "count", main='Frequency UG Campus Age', xlab='Age',
          col='darkblue', border = "white")
```



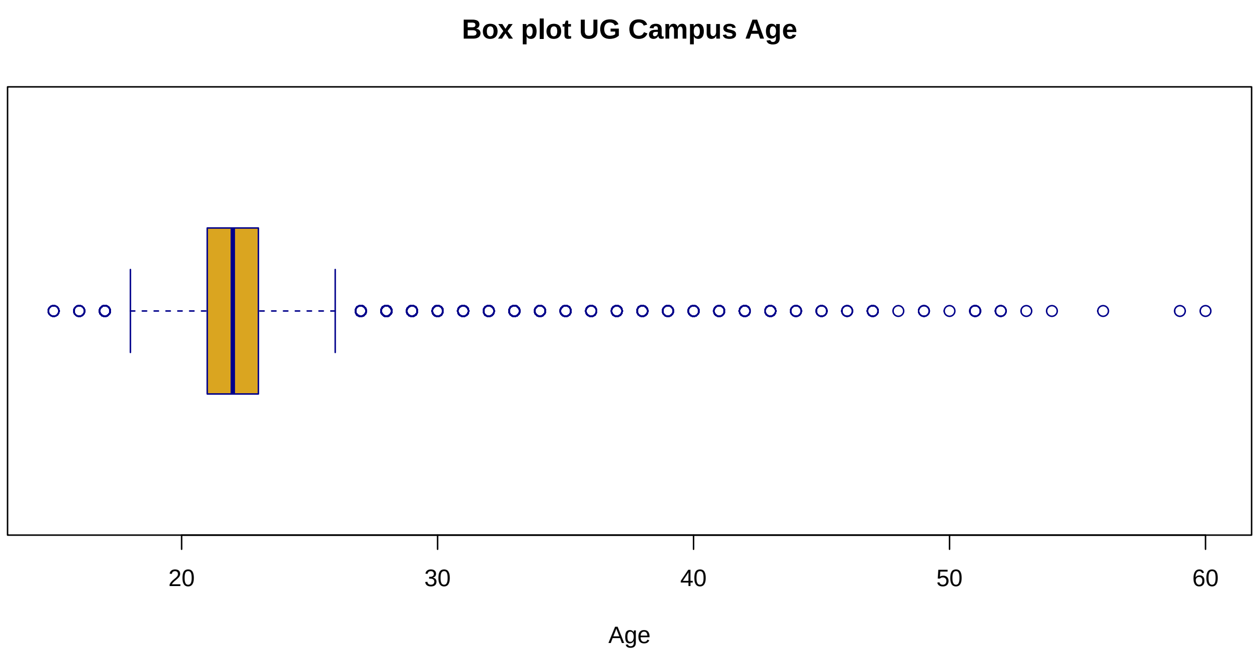
UG Campus - Historgram with density

```
ggplot(ug_desc_campus, aes(x=age)) +
 geom_histogram(aes(y=..density..), binwidth= 1, colour="white", fill="steelblue")+
 geom_density(alpha=.2, fill="lightblue") +
geom_vline(aes(xintercept=mean(age)), color="yellow", linetype="dashed") +
geom_vline(aes(xintercept=median(age)), color="chartreuse", linetype="dashed") +
labs(x="Age", y="Density")
```



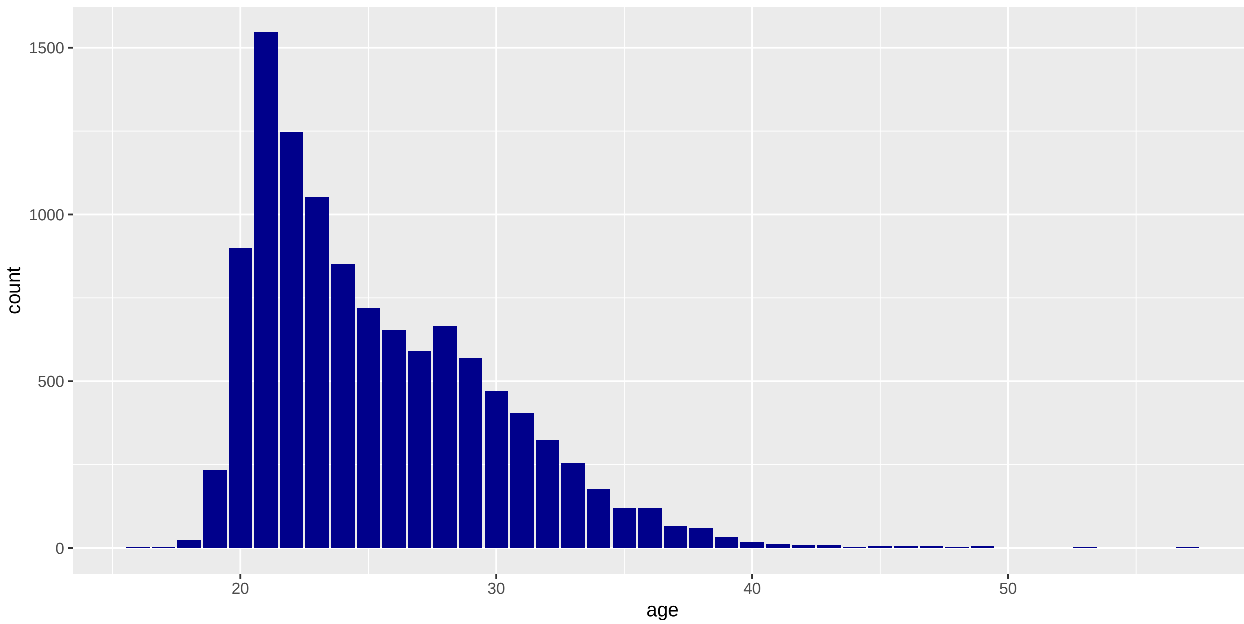
UG Campus - Box plot

```
boxplot(ug_desc_campus$age,
main = "Box plot UG Campus Age", xlab = "Age", col = "goldenrod", border = "darkblue",
horizontal = TRUE, notch = FALSE)
```



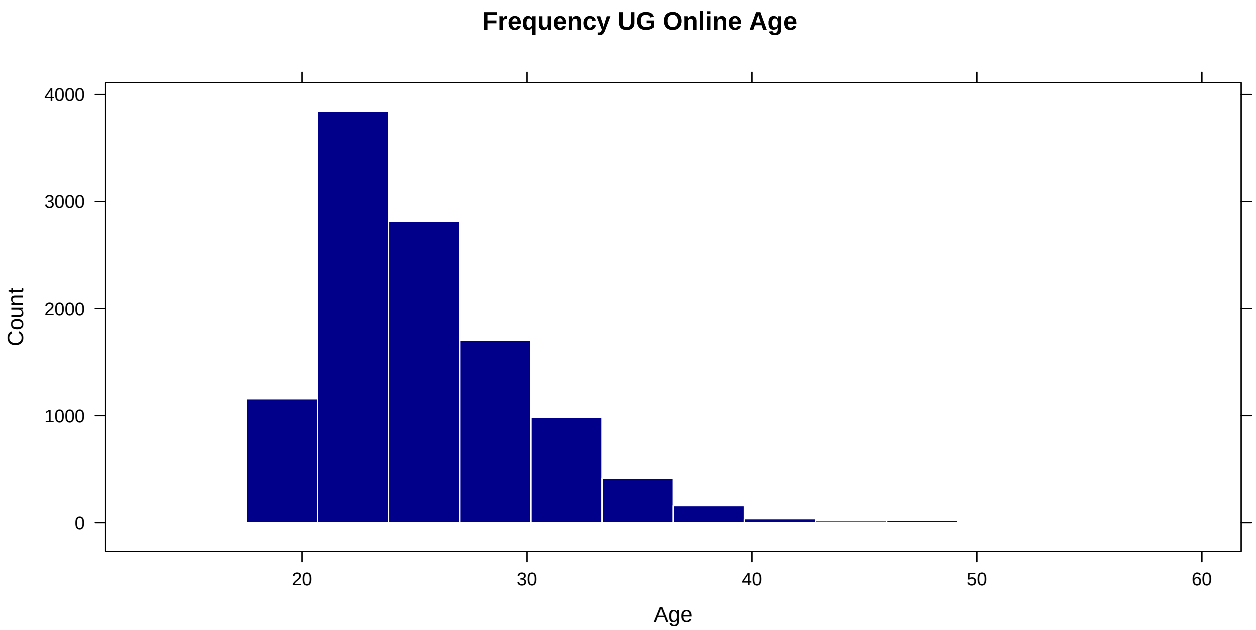
UG Online - Frequency

```
ggplot(ug_desc_online, aes(age)) + geom_bar(fill = "darkblue")
```



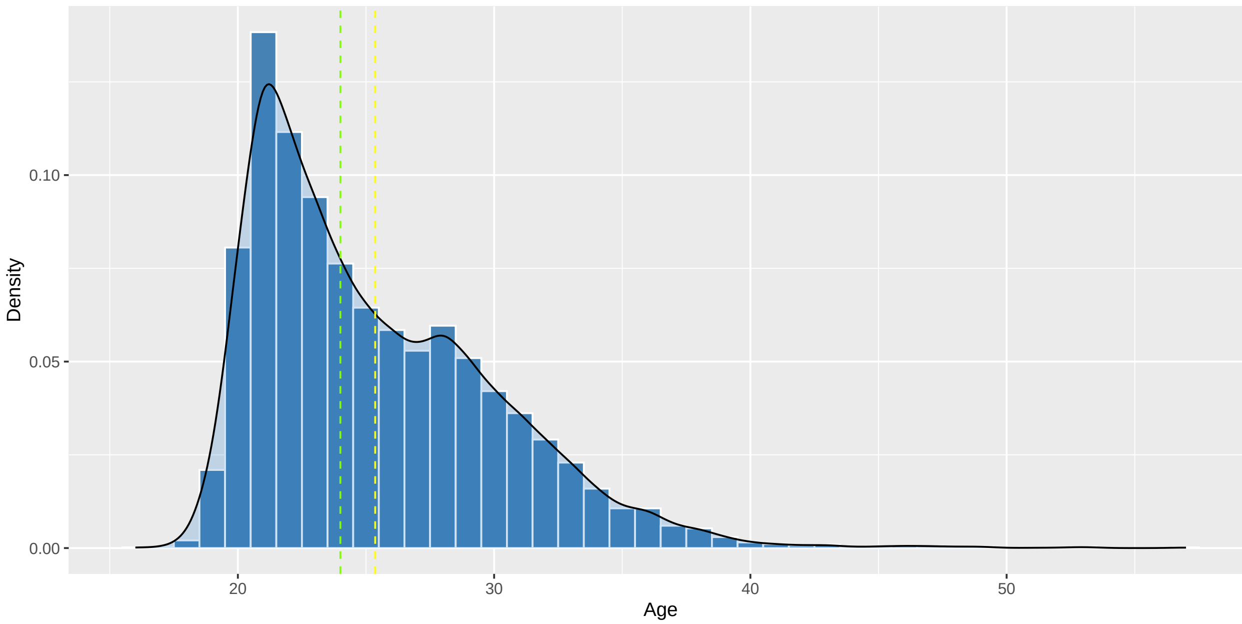
***UG Online - Historigram"**

```
histogram(ug_desc_online$age,
          type = "count", main='Frequency UG Online Age', xlab='Age', col='darkblue',
          border = "white")
```



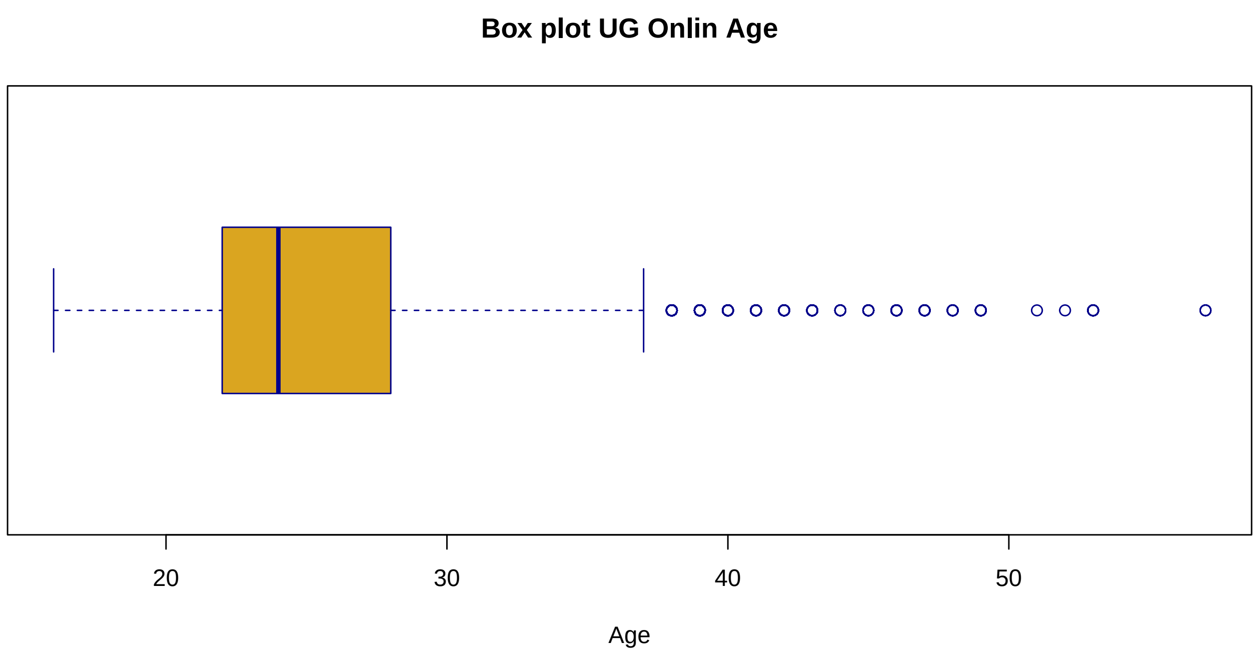
UG Online - Histogram with density

```
ggplot(ug_desc_online, aes(x=age)) +
 geom_histogram(aes(y=..density..), binwidth= 1, colour="white", fill="steelblue")+
 geom_density(alpha=.2, fill="dodgerblue3") +
geom_vline(aes(xintercept=mean(age)), color="yellow", linetype="dashed") +
  geom_vline(aes(xintercept=median(age)), color="chartreuse", linetype="dashed") +
  labs(x="Age", y="Density")
```



UG Online - Box plot

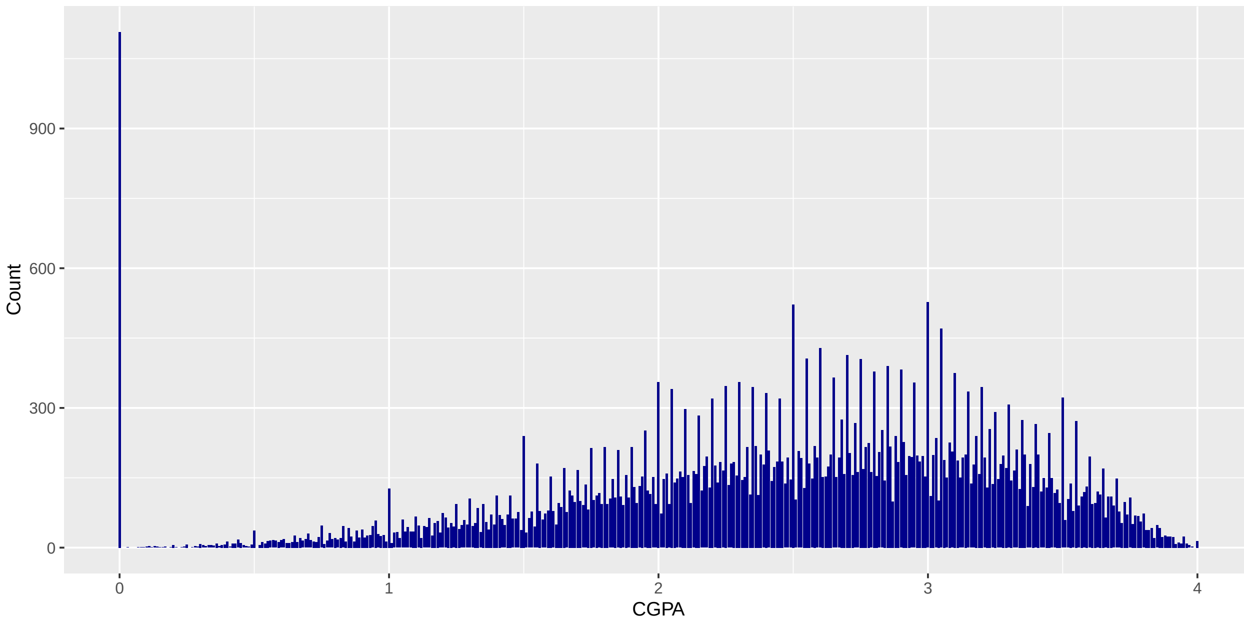
```
boxplot(ug_desc_online$age,
main = "Box plot UG Onlin Age", xlab = "Age", col = "goldenrod", border = "darkblue",
horizontal = TRUE, notch = FALSE)
```



CGPA

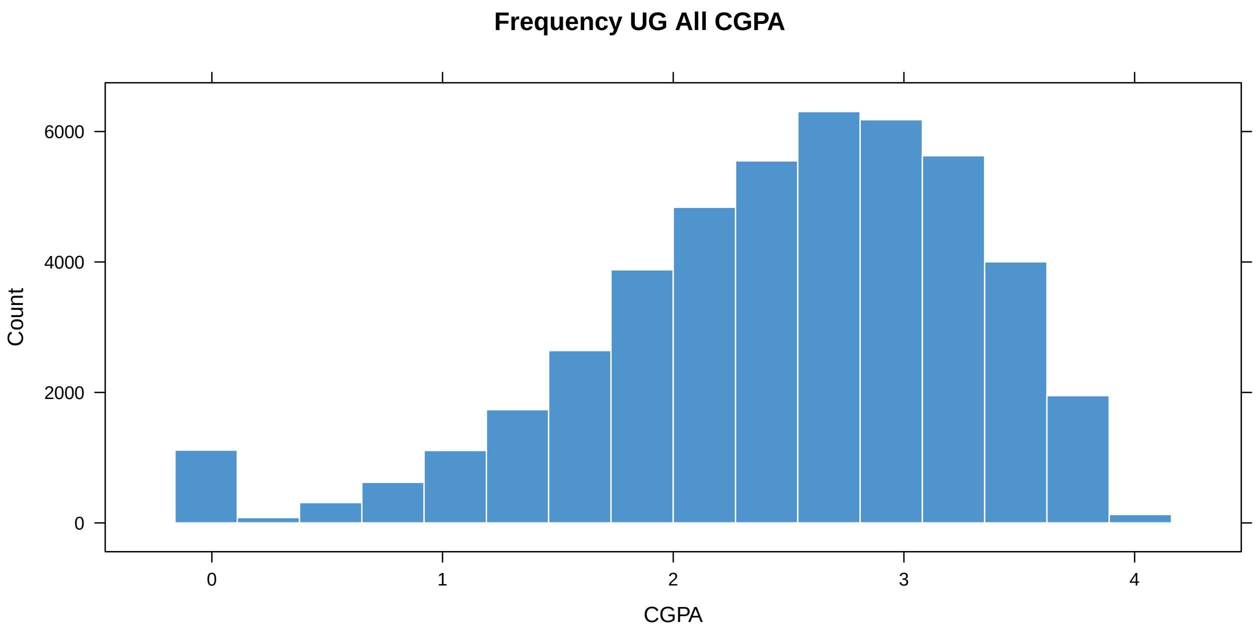
UG Dataset - Frequency

```
ggplot(ug_desc_all, aes(cgpa)) + geom_bar(fill = "darkblue") +
   xlab("CGPA") + ylab("Count")
```



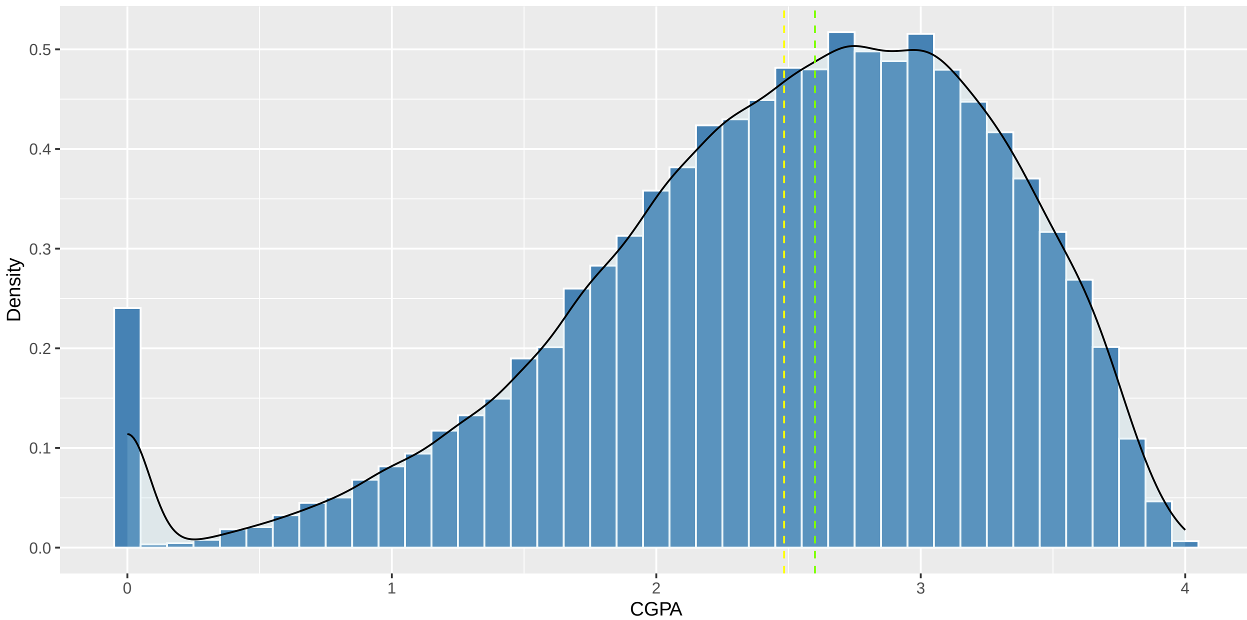
UG Dataset - Histogram

```
histogram(ug_desc_all$cgpa,
          type = "count", main='Frequency UG All CGPA',  xlab='CGPA',
          col='steelblue3', border = "white")
```



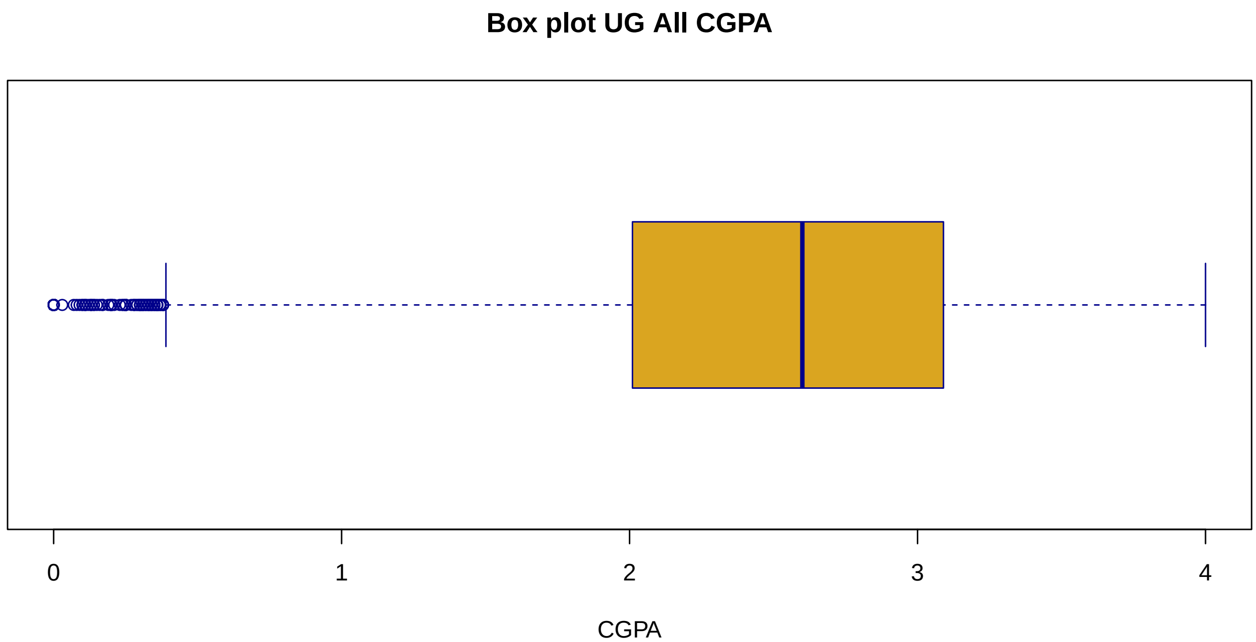
UG Dataset - Histogram with density

```
ggplot(ug_desc_all, aes(x=cgpa)) +
 geom_histogram(aes(y=..density..), binwidth= .10, colour="white", fill="steelblue")+
 geom_density(alpha=.2, fill="lightblue") +
geom_vline(aes(xintercept=mean(cgpa)), color="yellow", linetype="dashed") +
  geom_vline(aes(xintercept=median(cgpa)), color="chartreuse", linetype="dashed") +
  labs(x="CGPA", y="Density")
```



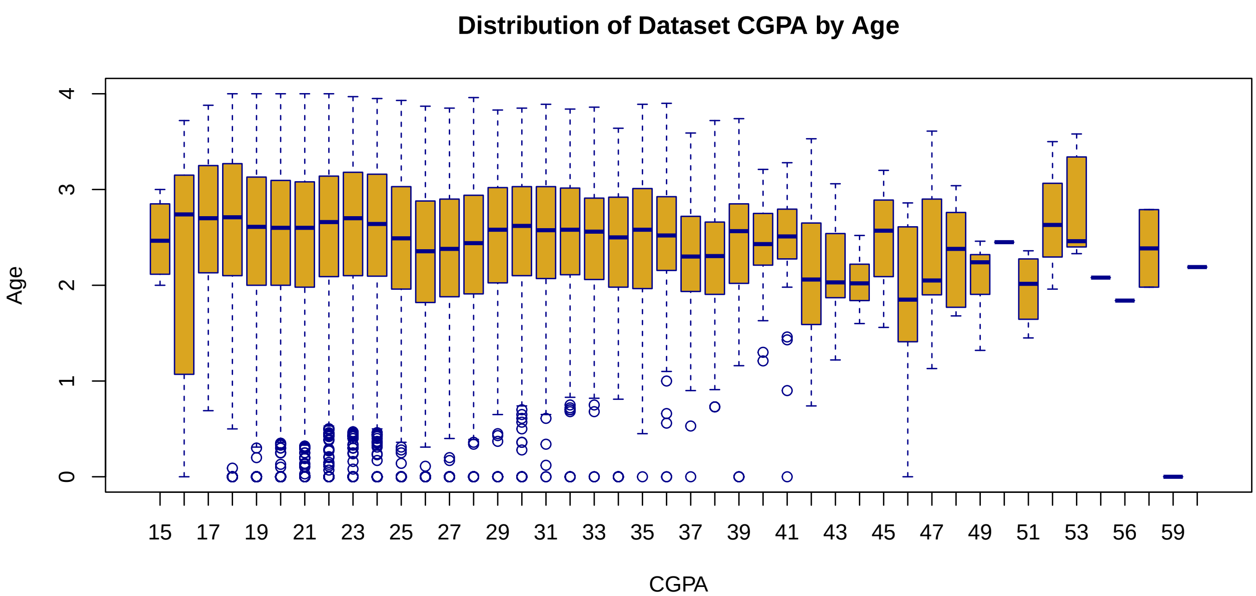
UG Dataset - Box plot

```
boxplot(ug_desc_all$cgpa,
main = "Box plot UG All CGPA", xlab = "CGPA", col = "goldenrod", border = "darkblue",
horizontal = TRUE, notch = FALSE)
```



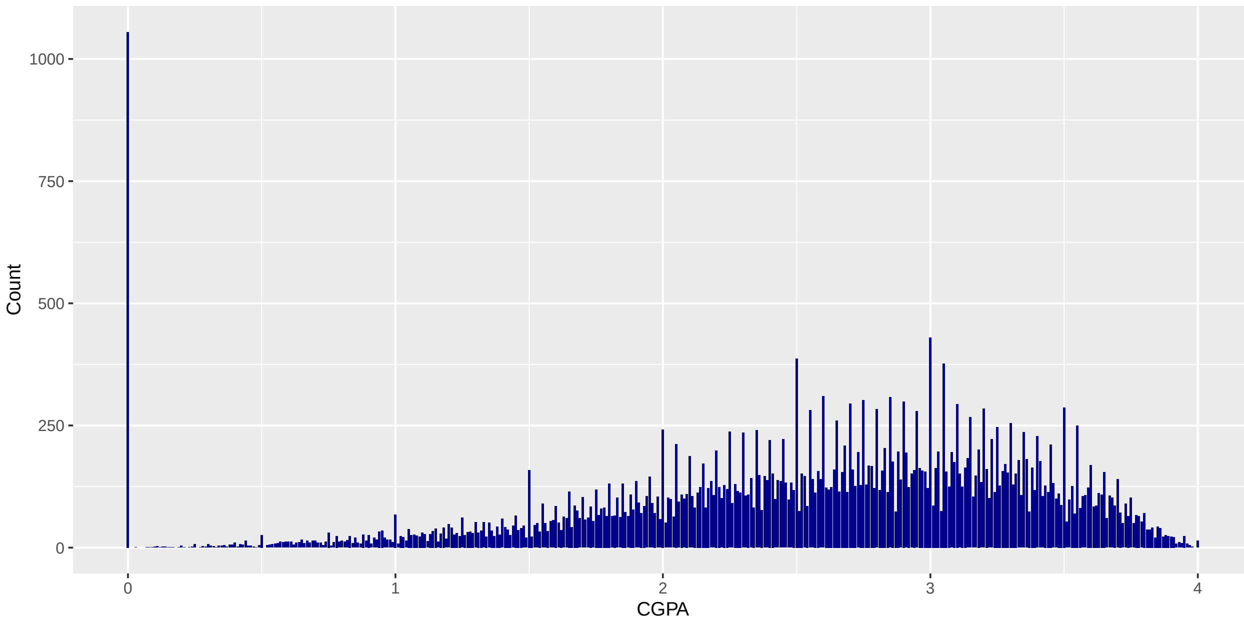
**UG Dataset - Box plot (CGPA by Age)*

```
boxplot(cgpa~age,
data=ug_desc_all,
main="Distribution of Dataset CGPA by Age", xlab="CGPA", ylab="Age", col="goldenrod",
border="darkblue")
```



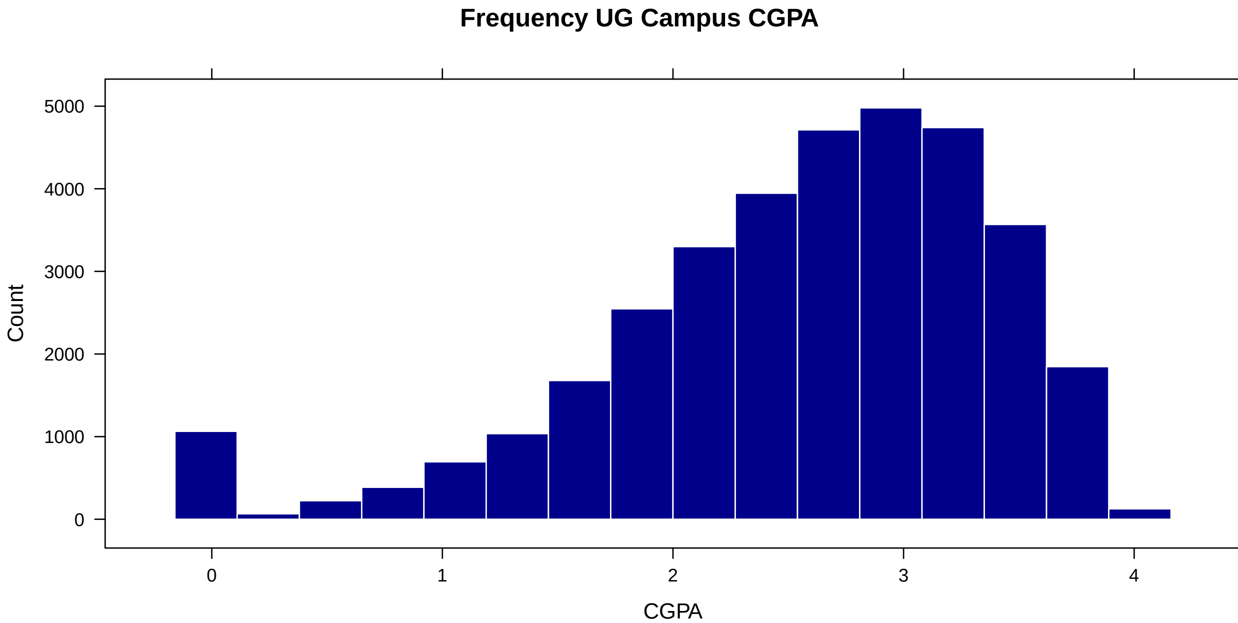
UG Campus - Frequency

```
ggplot(ug_desc_campus, aes(cgpa)) + xlab("CGPA") + ylab("Count") +
  geom_bar(fill = "darkblue")
```



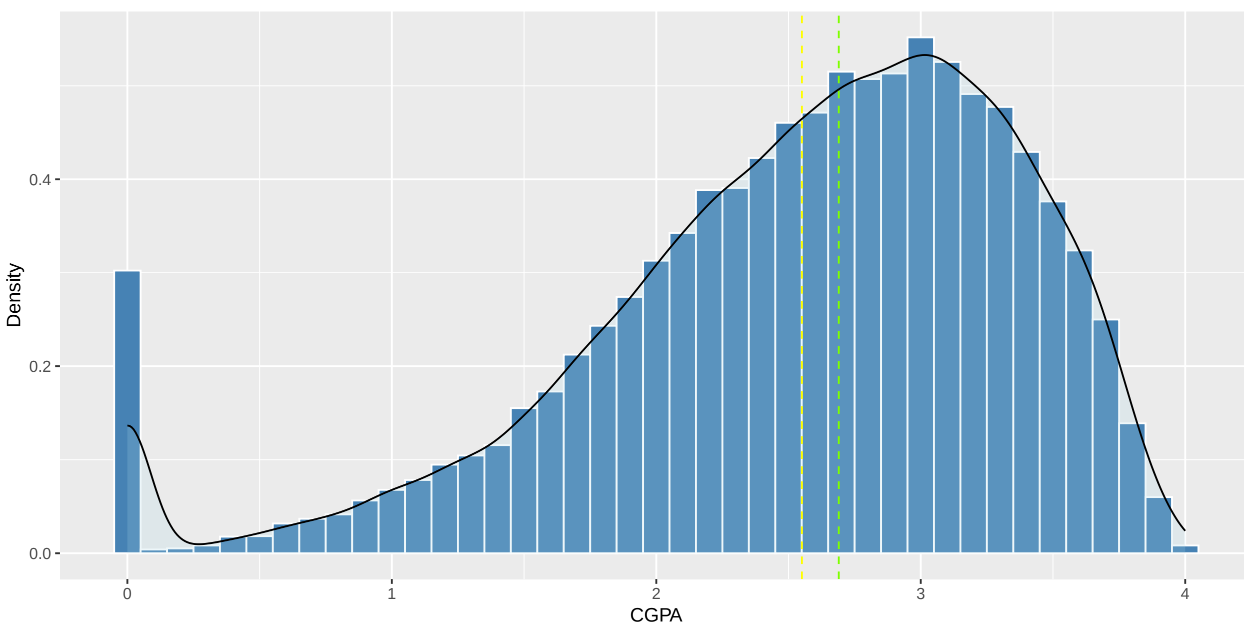
UG Campus - Histogram

```
histogram(ug_desc_campus$cgpa,
          type = "count", main='Frequency UG Campus CGPA', xlab='CGPA',
          col='darkblue', border = "white")
```



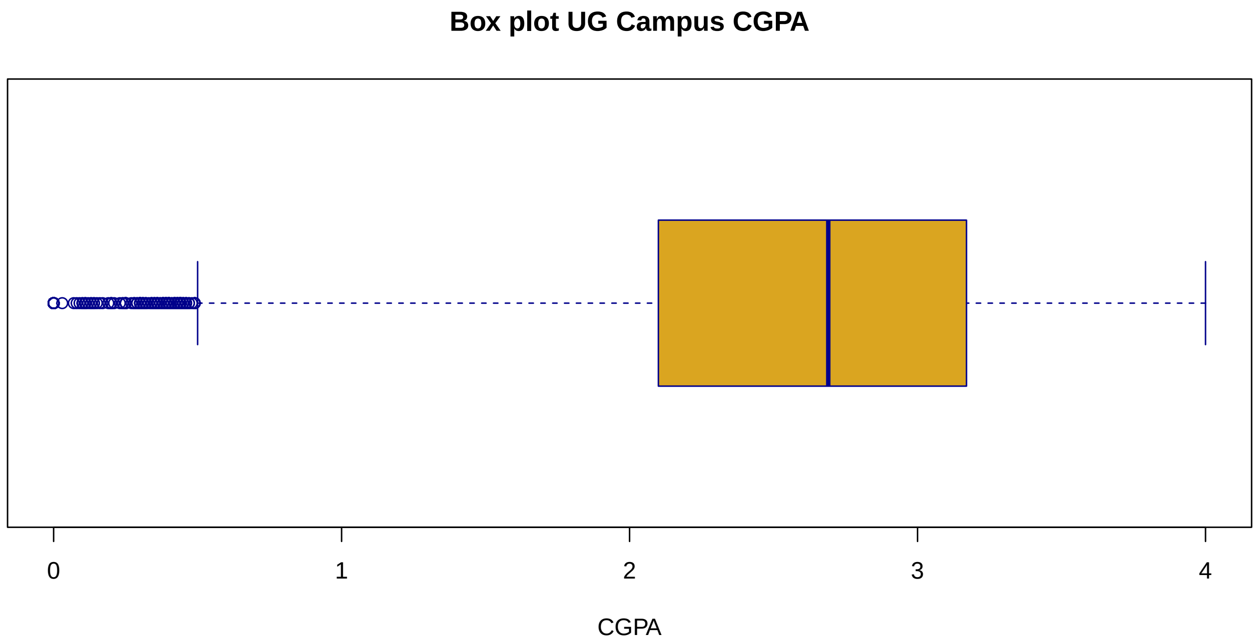
UG Campus - Histogram with density

```
ggplot(ug_desc_campus, aes(x=cgpa)) +
 geom_histogram(aes(y=..density..), binwidth= .10, colour="white", fill="steelblue")+
 geom_density(alpha=.2, fill="lightblue") +
geom_vline(aes(xintercept=mean(cgpa)), color="yellow", linetype="dashed") +
geom_vline(aes(xintercept=median(cgpa)), color="chartreuse", linetype="dashed") +
labs(x="CGPA", y="Density")
```



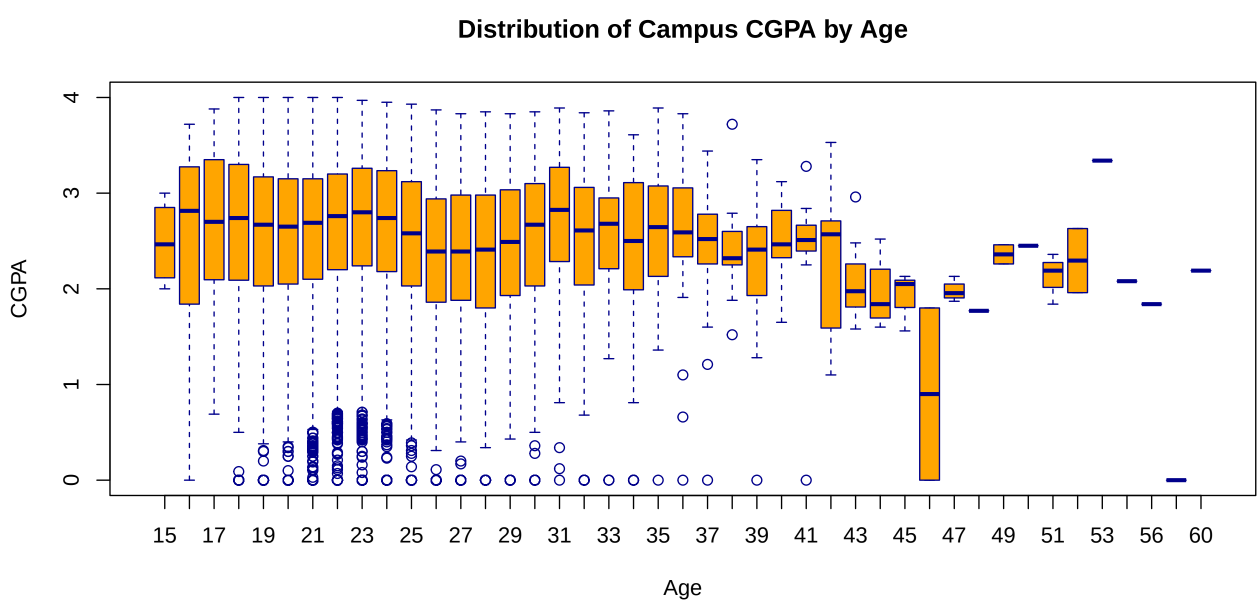
UG Campus - Box plot

```
boxplot(ug_desc_campus$cgpa,
main = "Box plot UG Campus CGPA", xlab = "CGPA", col = "goldenrod", border = "darkblue",
horizontal = TRUE, notch = FALSE)
```



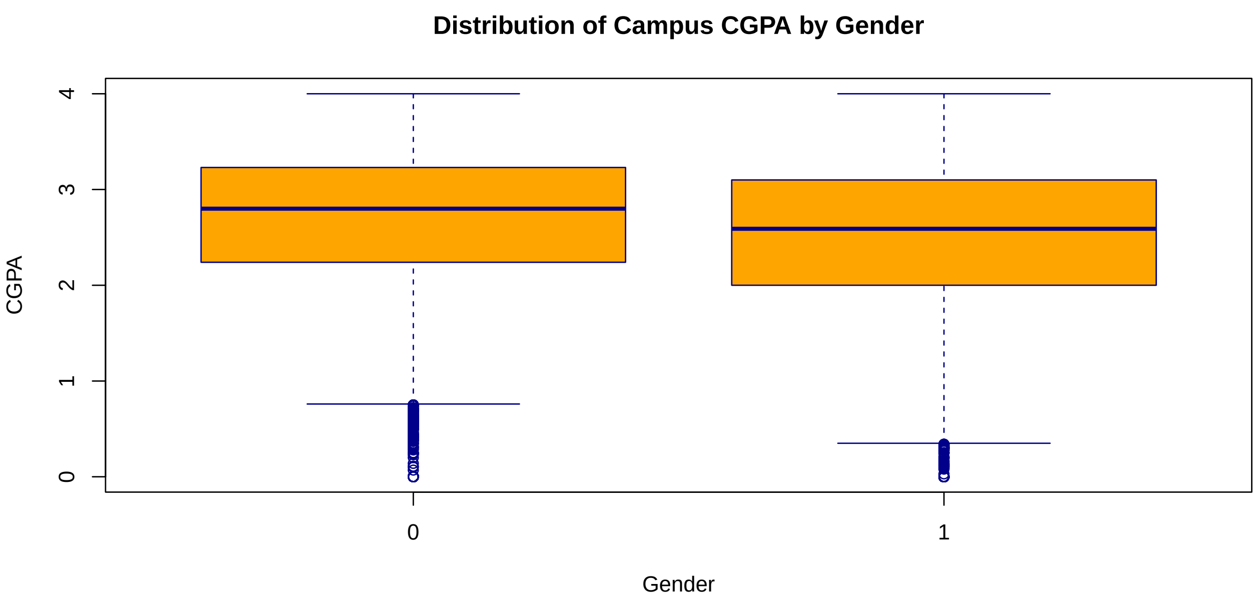
UG Campus - Box plot (CGPA by Age)

```
boxplot(cgpa~age,
data=ug_desc_campus,
main="Distribution of Campus CGPA by Age", xlab="Age", ylab="CGPA", col="orange",
border="darkblue")
```



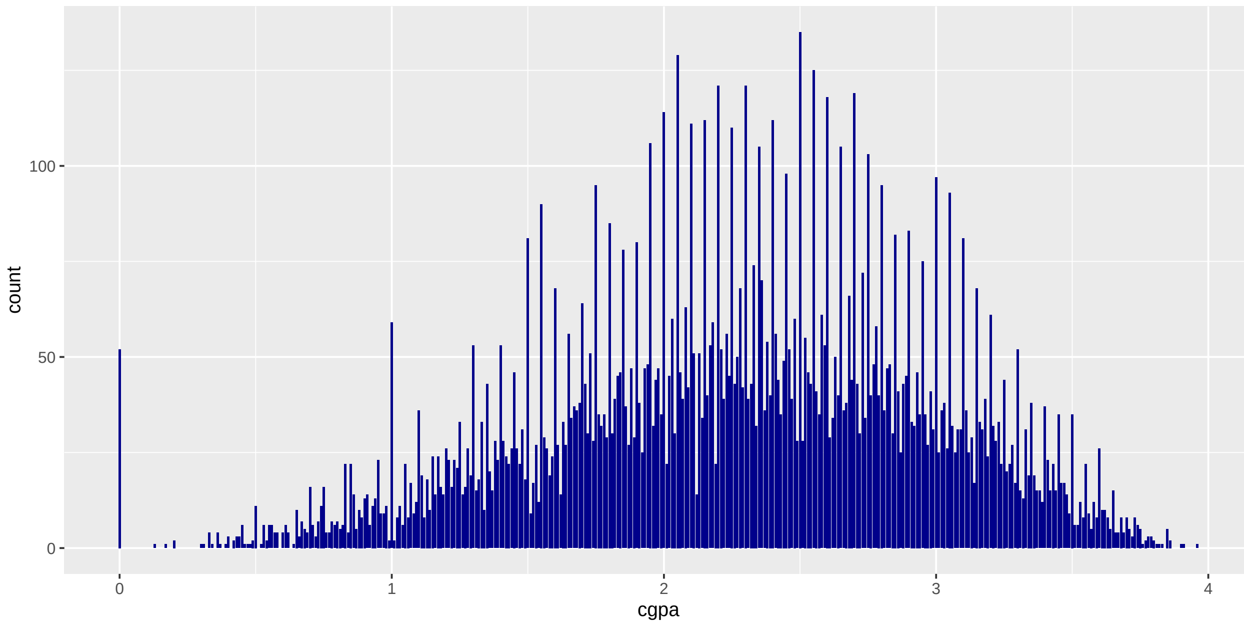
UG Campus - Box plot (CGPA by Geder)

```
boxplot(cgpa~gender,
data=ug_desc_campus,
main="Distribution of Campus CGPA by Gender", xlab="Gender", ylab="CGPA", col="orange",
border="darkblue")
```



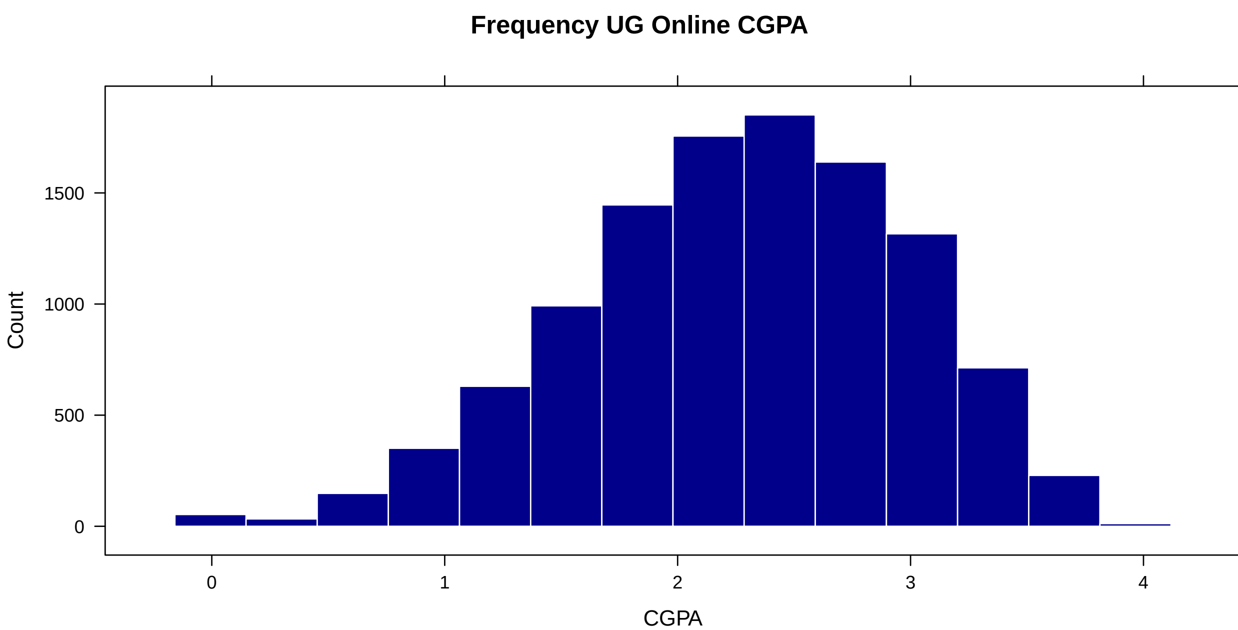
UG Online - Frquency

```
ggplot(ug_desc_online, aes(cgpa)) + geom_bar(fill = "darkblue")
```



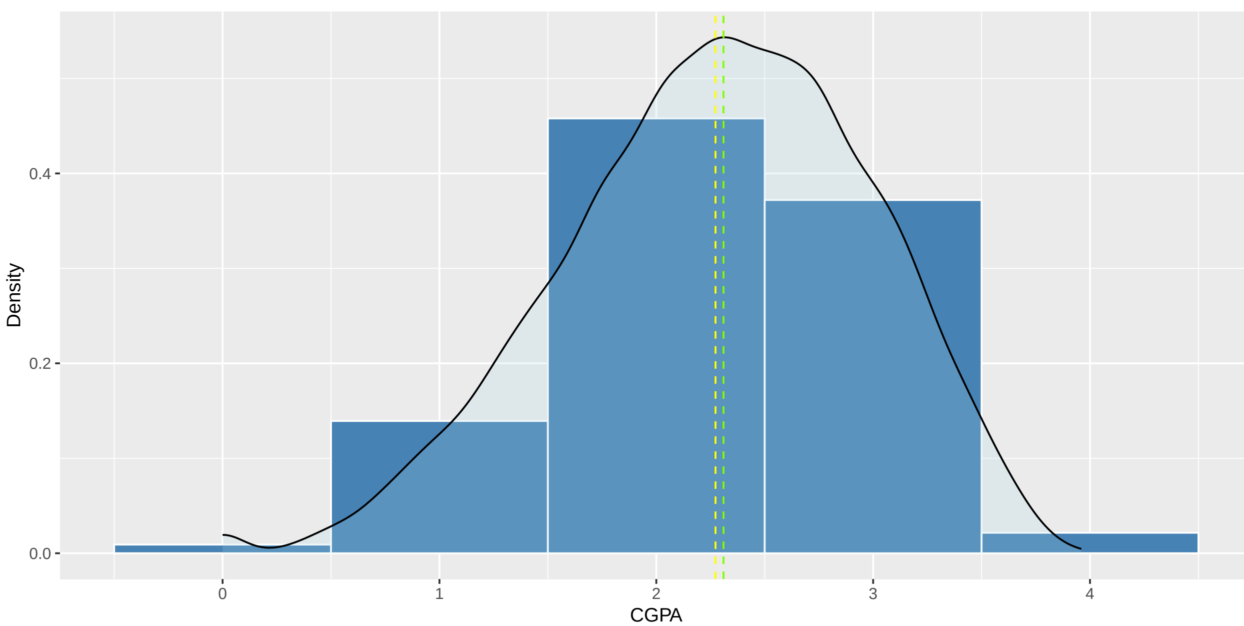
UG Online - Histogram

```
histogram(ug_desc_online$cgpa,
          type = "count", main='Frequency UG Online CGPA', xlab='CGPA', col='darkblue',
          border = "white")
```



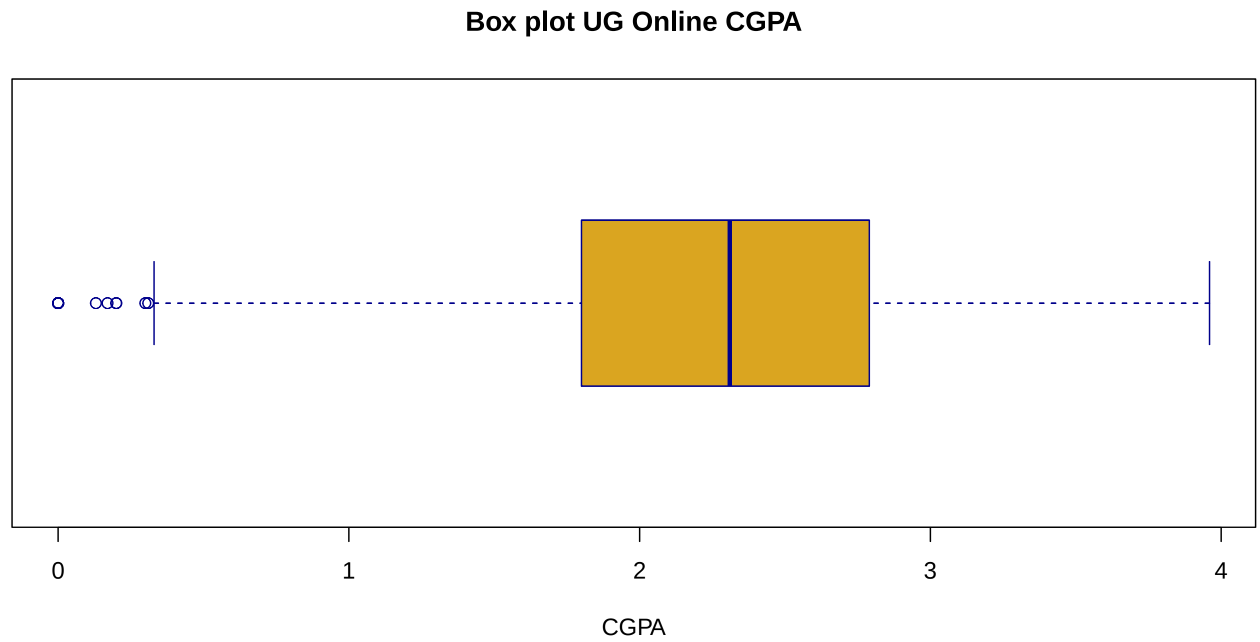
UG Online - Histogram with density

```
ggplot(ug_desc_online, aes(x=cgpa)) +
 geom_histogram(aes(y=..density..), binwidth= 1, colour="white", fill="steelblue")+
 geom_density(alpha=.2, fill="lightblue") +
geom_vline(aes(xintercept=mean(cgpa)), color="yellow", linetype="dashed") +
  geom_vline(aes(xintercept=median(cgpa)), color="chartreuse", linetype="dashed") +
  labs(x="CGPA", y="Density")
```



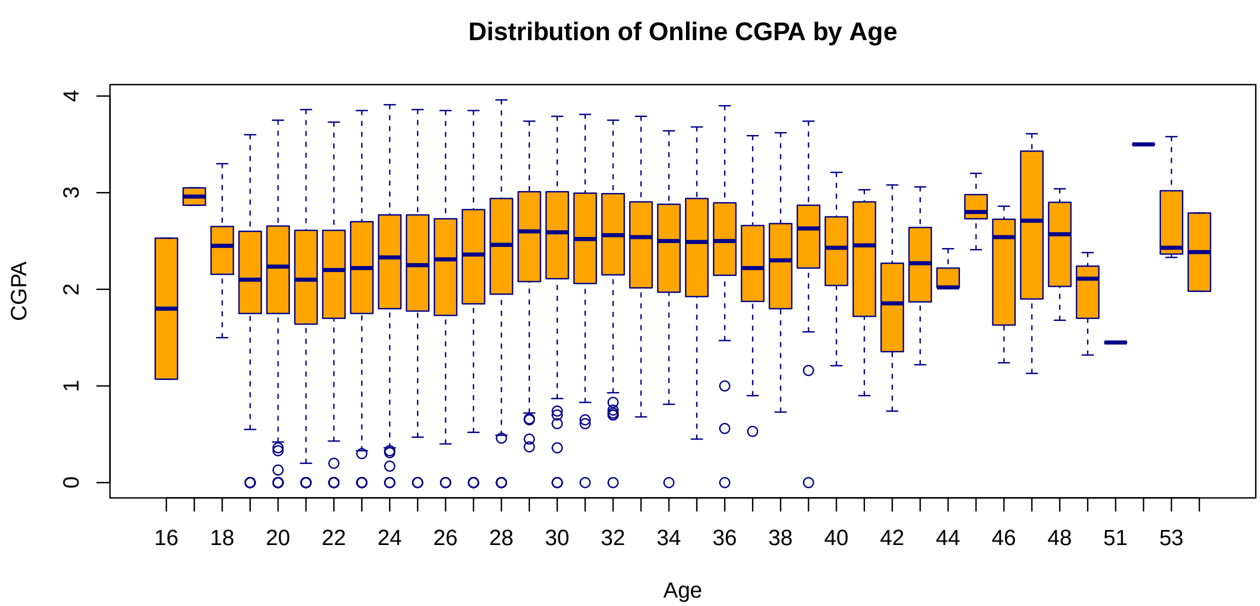
UG Online - Box plot

```
boxplot(ug_desc_online$cgpa, main = "Box plot UG Online CGPA", xlab = "CGPA",
        col = "goldenrod", border = "darkblue", horizontal = TRUE, notch = FALSE)
```



UG Online - Box plot (CGPA by Age)

```
boxplot(cgpa~age, data=ug_desc_online, main="Distribution of Online CGPA by Age",
xlab="Age", ylab="CGPA", col="orange", border="darkblue" )
```



Year/Level

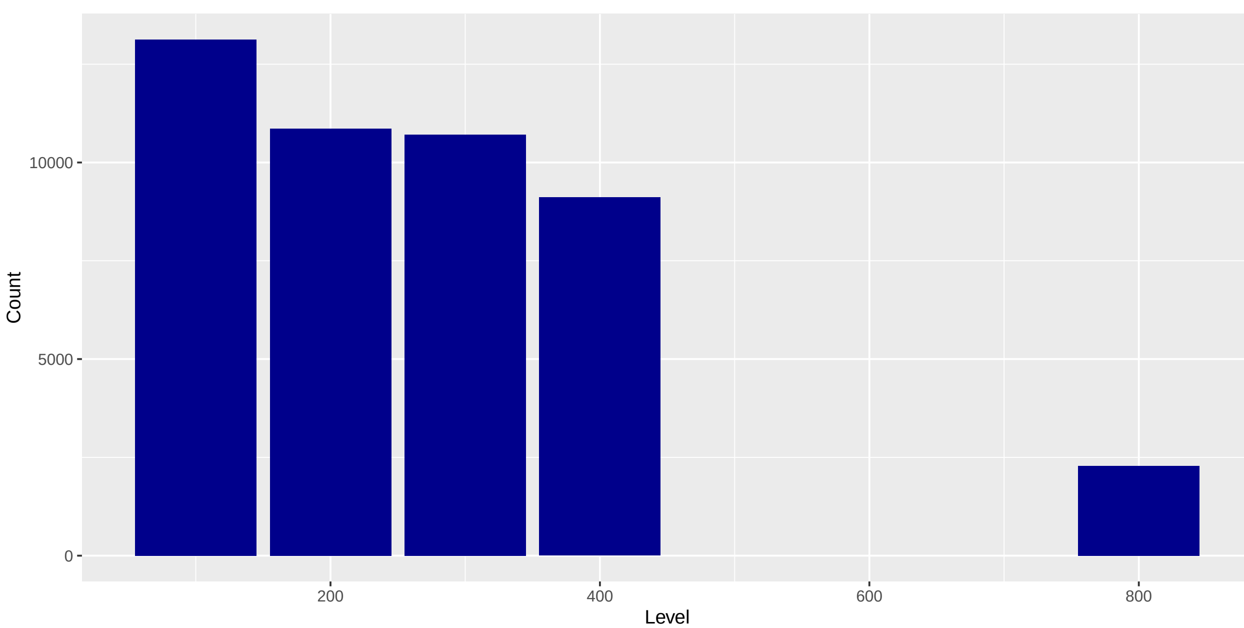
UG Dataset - Frequency

```
freq(ug_desc_all$level, plain.ascii = TRUE, style = 'grid')
```

Frequencies
ug_desc_all$level
Type: Numeric

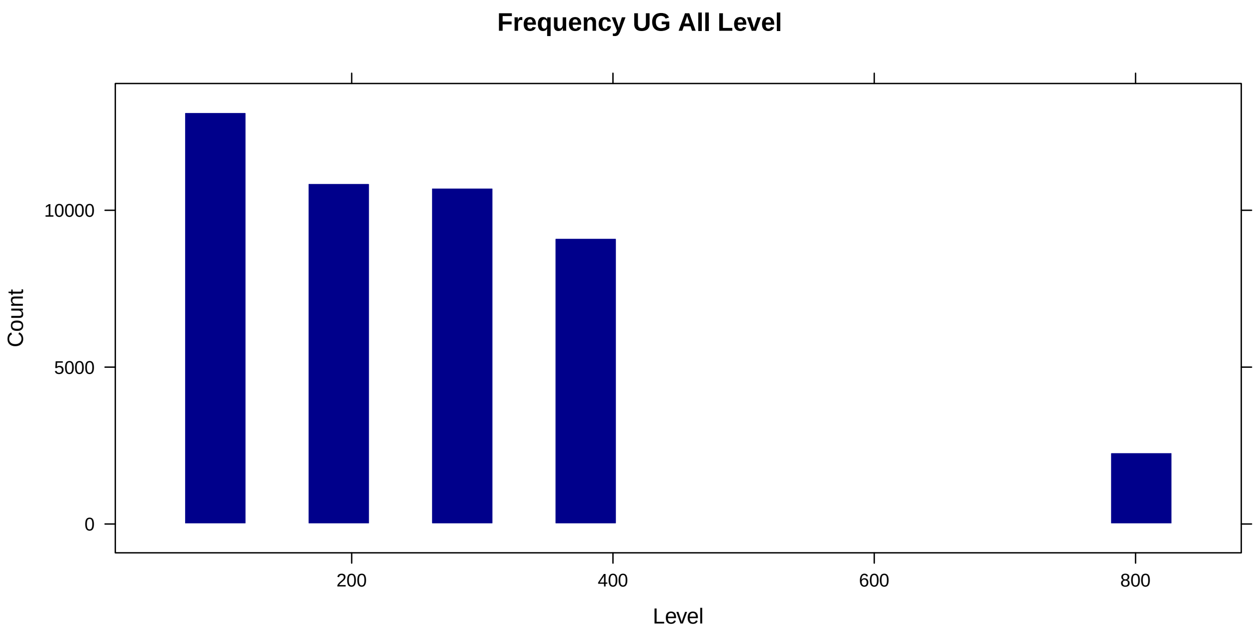
	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
100	13122	28.47	28.47	28.47	28.47
200	10860	23.56	52.04	23.56	52.04
300	10714	23.25	75.28	23.25	75.28
400	9112	19.77	95.06	19.77	95.06
800	2279	4.94	100.00	4.94	100.00
<NA>	0			0.00	100.00
Total	46087	100.00	100.00	100.00	100.00

```
ggplot(ug_desc_all, aes(level)) + xlab("Level") + ylab("Count") +
  geom_bar(fill = "darkblue")
```



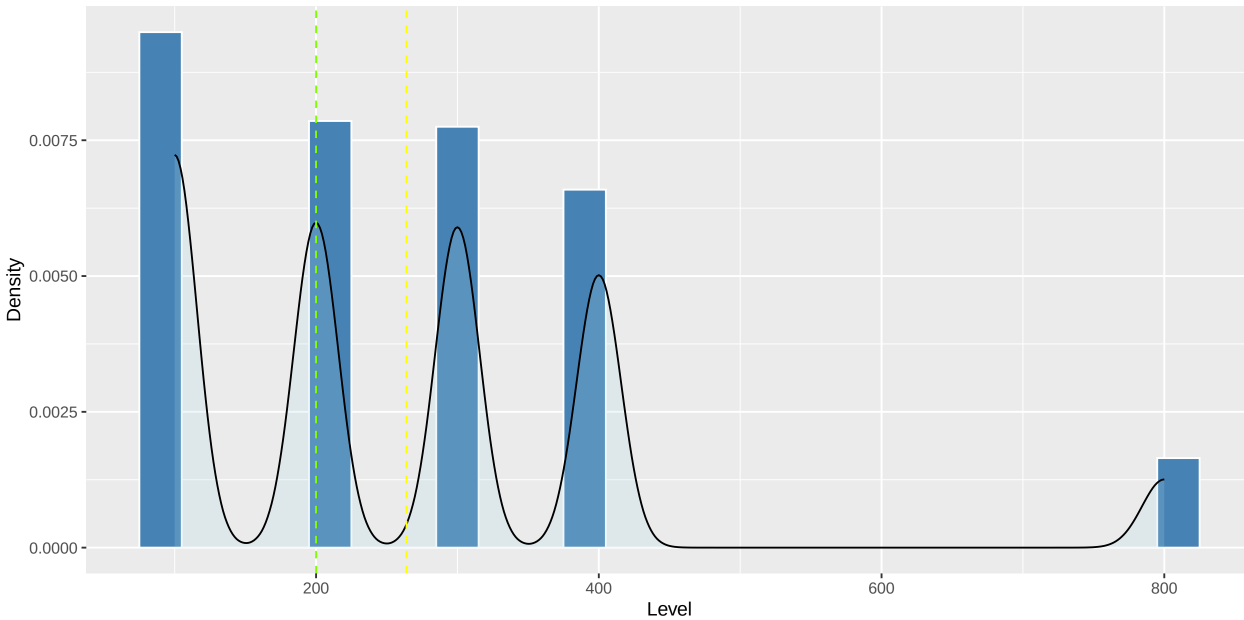
UG Dataset - Histogram

```
histogram(ug_desc_all$level, type = "count", main='Frequency UG All Level',
          xlab='Level', col='darkblue', border = "white")
```



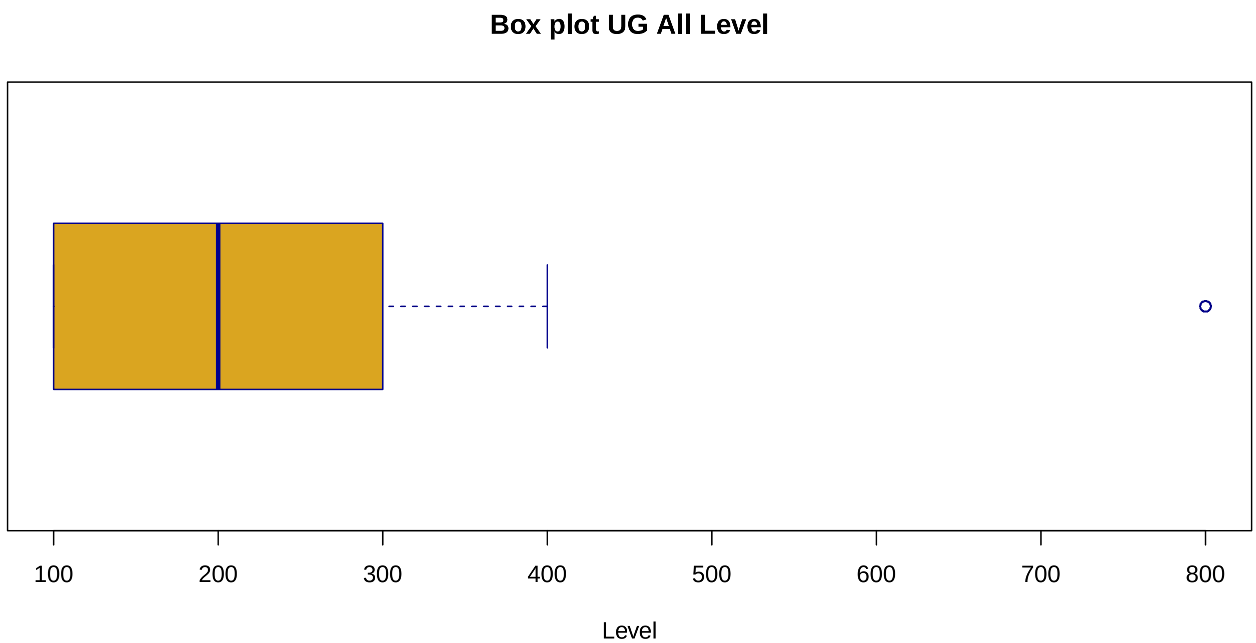
UG Dataset - Histogram with density

```
ggplot(ug_desc_all, aes(x=level)) +
 geom_histogram(aes(y=..density..), binwidth= 30, colour="white", fill="steelblue")+
 geom_density(alpha=.2, fill="lightblue") +
geom_vline(aes(xintercept=mean(level)), color="yellow", linetype="dashed") +
  geom_vline(aes(xintercept=median(level)), color="chartreuse", linetype="dashed") +
  labs(x="Level", y="Density")
```



UG Dataset - Box plot

```
boxplot(ug_desc_all$level, main = "Box plot UG All Level", xlab = "Level",
        col = "goldenrod", border = "darkblue", horizontal = TRUE, notch = FALSE)
```



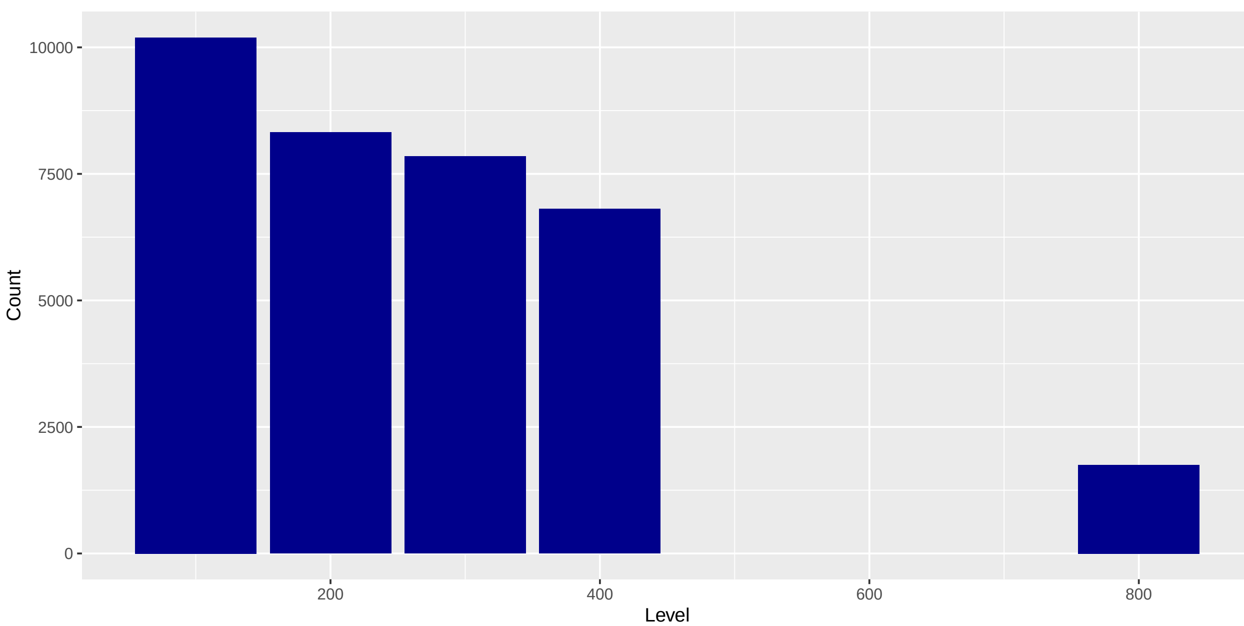
UG Campus - Frquency

```
freq(ug_desc_campus$level, plain.ascii = TRUE, style = 'grid')
```

Frequencies
ug_desc_campus$level
Type: Numeric

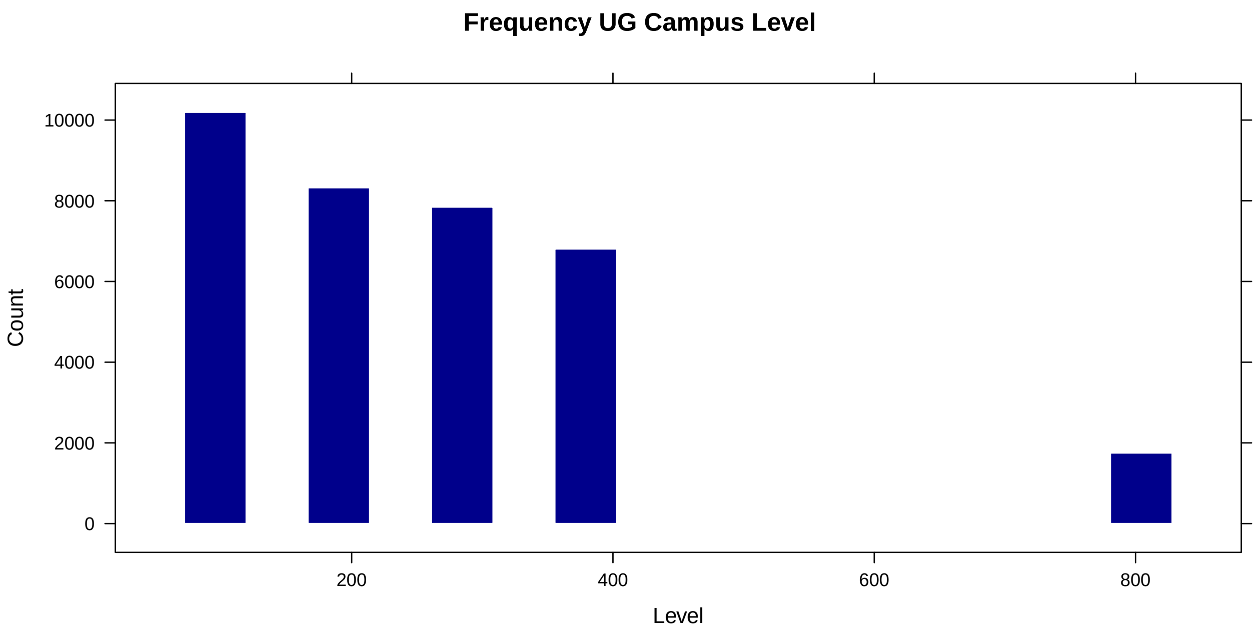
	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
100	10194	29.19	29.19	29.19	29.19
200	8324	23.84	53.03	23.84	53.03
300	7844	22.46	75.50	22.46	75.50
400	6806	19.49	94.99	19.49	94.99
800	1750	5.01	100.00	5.01	100.00
<NA>	0			0.00	100.00
Total	34918	100.00	100.00	100.00	100.00

```
ggplot(ug_desc_campus, aes(level)) + xlab("Level") + ylab("Count") +
  geom_bar(fill = "darkblue")
```



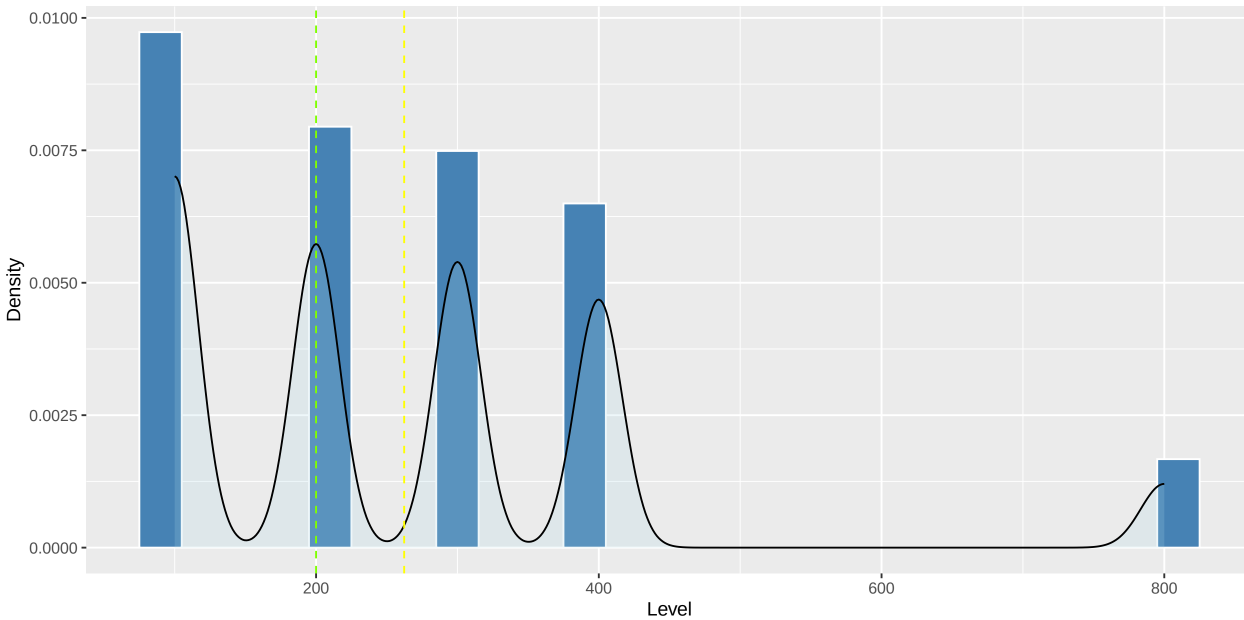
UG Campus - Histogram

```
histogram(ug_desc_campus$level, type = "count", main='Frequency UG Campus Level',
          xlab='Level', col='darkblue', border = "white")
```



UG Campus - Histogram with density

```
ggplot(ug_desc_campus, aes(x=level)) +
 geom_histogram(aes(y=..density..), binwidth= 30, colour="white", fill="steelblue")+
 geom_density(alpha=.2, fill="lightblue") +
geom_vline(aes(xintercept=mean(level)), color="yellow", linetype="dashed") +
  geom_vline(aes(xintercept=median(level)), color="chartreuse", linetype="dashed") +
  labs(x="Level", y="Density")
```



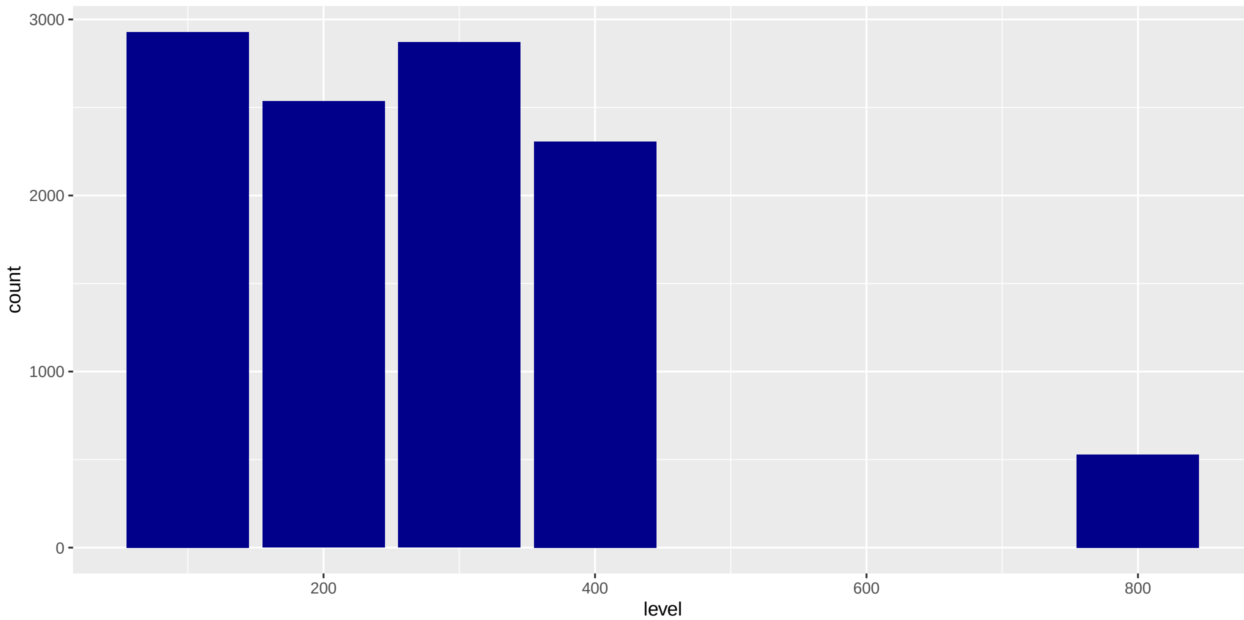
UG Online - Frequency

```
freq(ug_desc_online$level, plain.ascii = TRUE, style = 'grid')
```

Frequencies
ug_desc_online$level
Type: Numeric

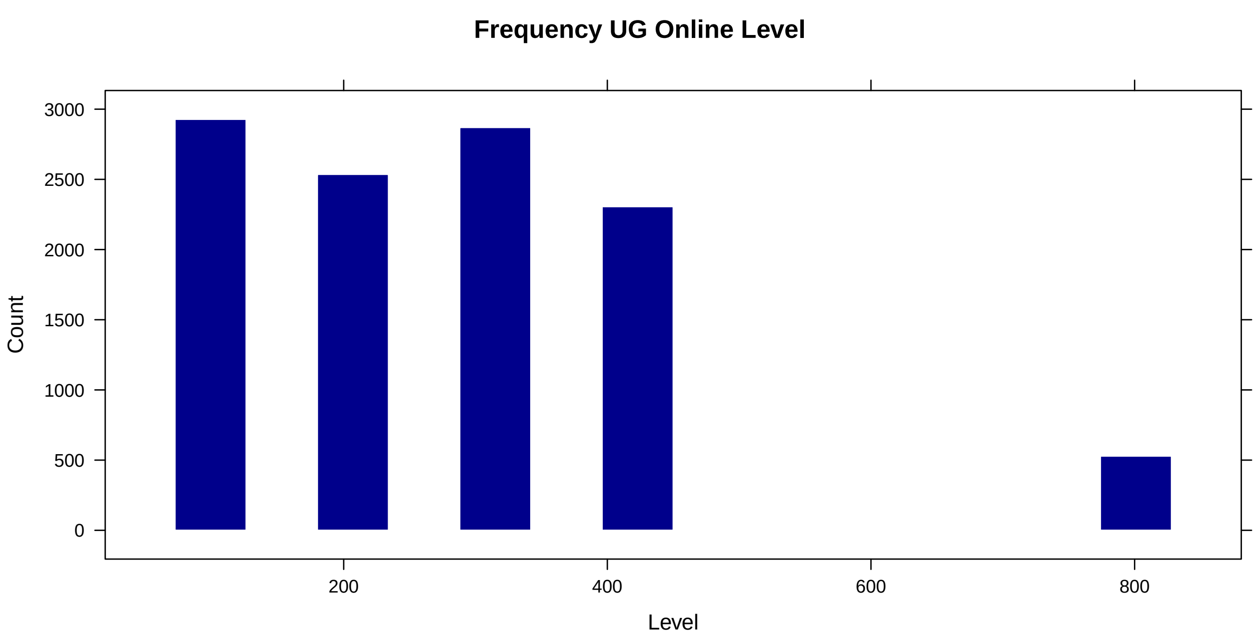
	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
100	2928	26.22	26.22	26.22	26.22
200	2536	22.71	48.92	22.71	48.92
300	2870	25.70	74.62	25.70	74.62
400	2306	20.65	95.26	20.65	95.26
800	529	4.74	100.00	4.74	100.00
<NA>	0			0.00	100.00
Total	11169	100.00	100.00	100.00	100.00

```
ggplot(ug_desc_online, aes(level)) + geom_bar(fill = "darkblue")
```



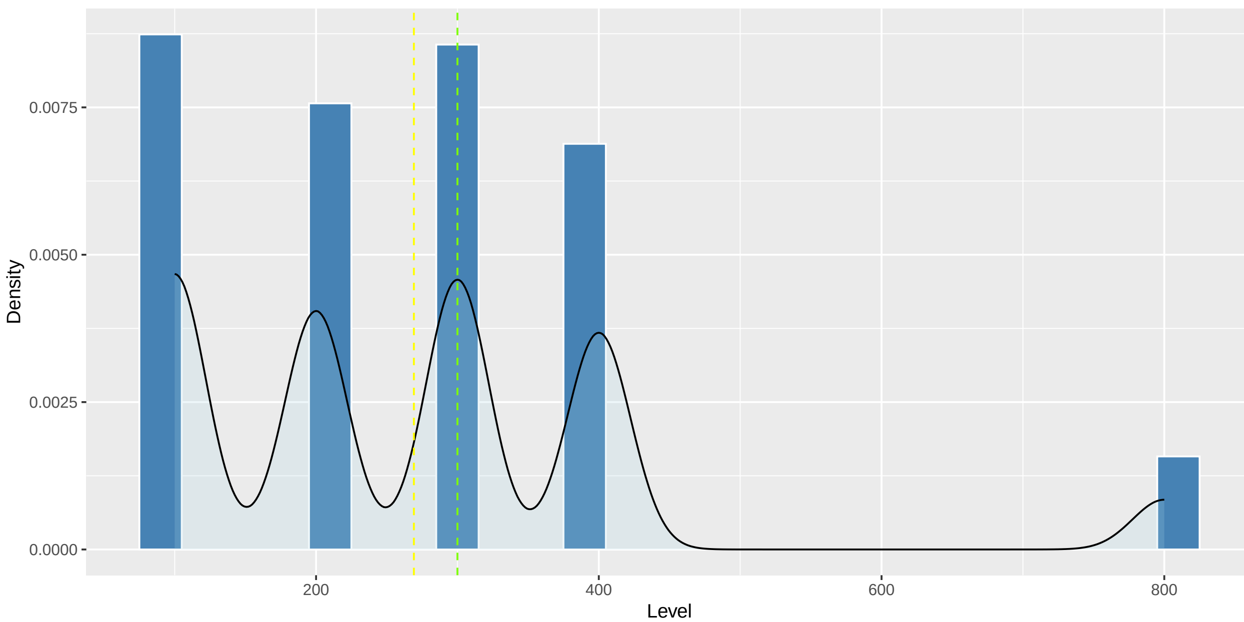
UG Online - Histogram

```
histogram(ug_desc_online$level, type = "count", main='Frequency UG Online Level',
          xlab='Level', col='darkblue', border = "white")
```



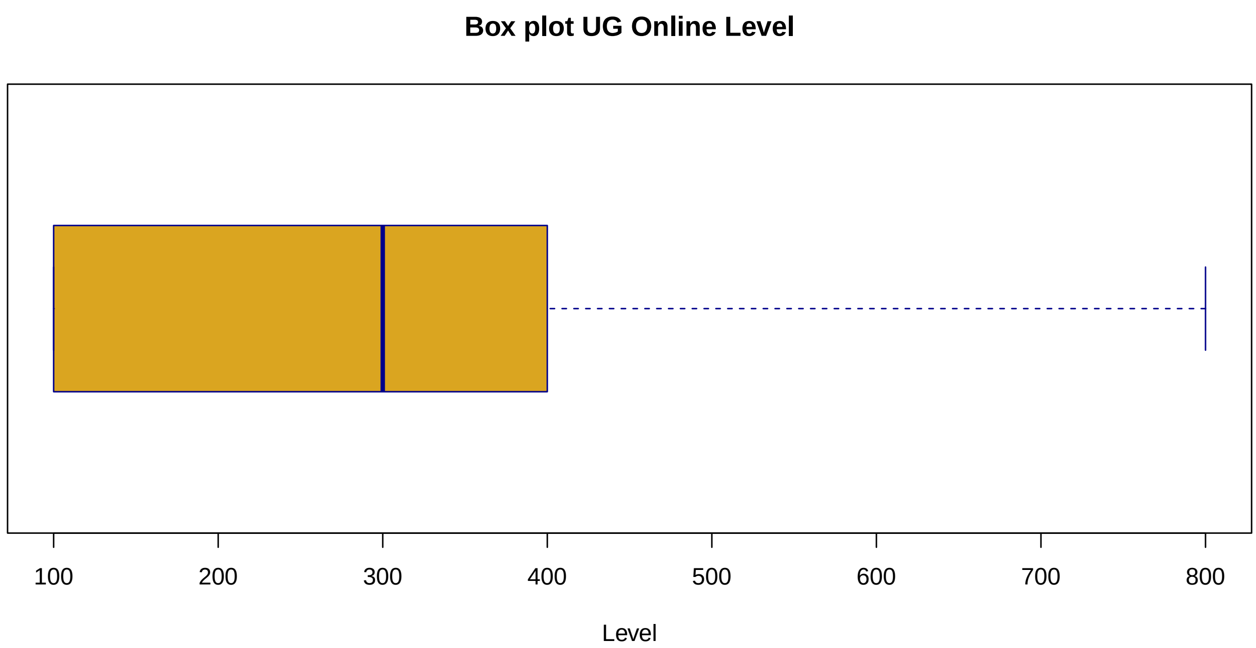
UG Online - Histogram with density

```
ggplot(ug_desc_online, aes(x=level)) +
 geom_histogram(aes(y=..density..), binwidth= 30, colour="white", fill="steelblue")+
 geom_density(alpha=.2, fill="lightblue") +
geom_vline(aes(xintercept=mean(level)), color="yellow", linetype="dashed") +
  geom_vline(aes(xintercept=median(level)), color="chartreuse", linetype="dashed") +
  labs(x="Level", y="Density")
```



UG Online - Box plot

```
boxplot(ug_desc_online$level, main = "Box plot UG Online Level", xlab = "Level",
col = "goldenrod", border = "darkblue", horizontal = TRUE, notch = FALSE)
```


Box plot UG Online Level
100
200
300
400
500
600
700
800
Level

Degree Program

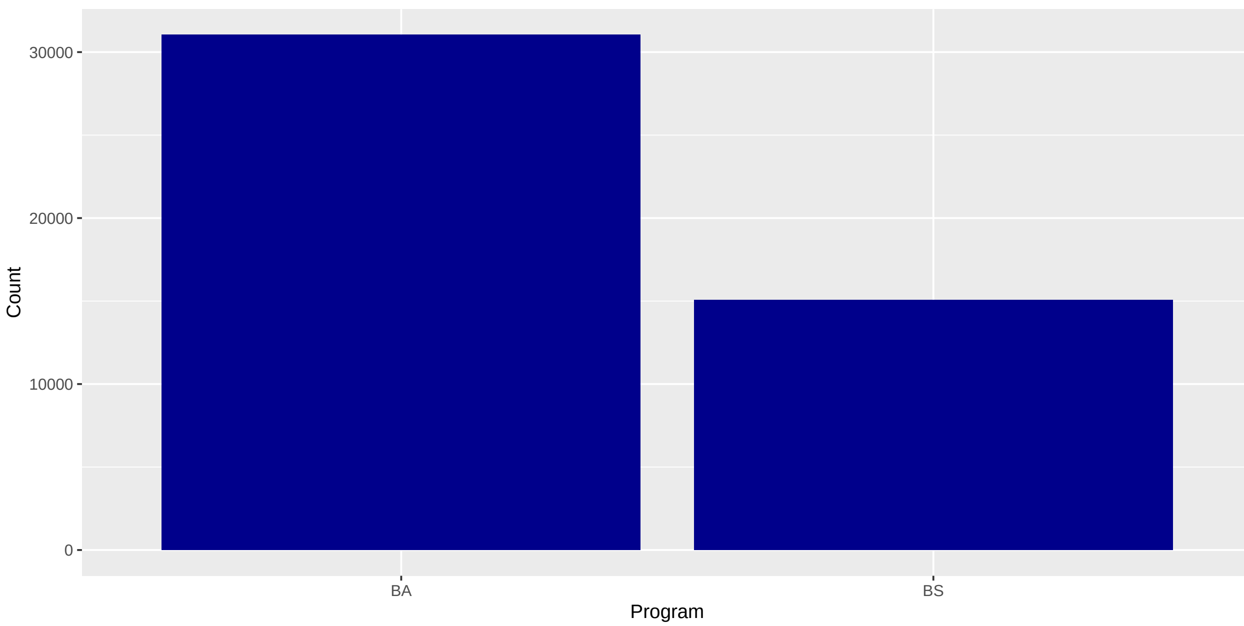
UG Dataset - Frequency

```
freq(ug_desc_all$prog, plain.ascii = TRUE, style = 'grid')
```

Frequencies
ug_desc_all$prog
Type: Character

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
BA	31036	67.34	67.34	67.34	67.34
BS	15051	32.66	100.00	32.66	100.00
<NA>	0			0.00	100.00
Total	46087	100.00	100.00	100.00	100.00

```
ggplot(ug_desc_all, aes(prog)) + xlab("Program") + ylab("Count") +
  geom_bar(fill = "darkblue")
```



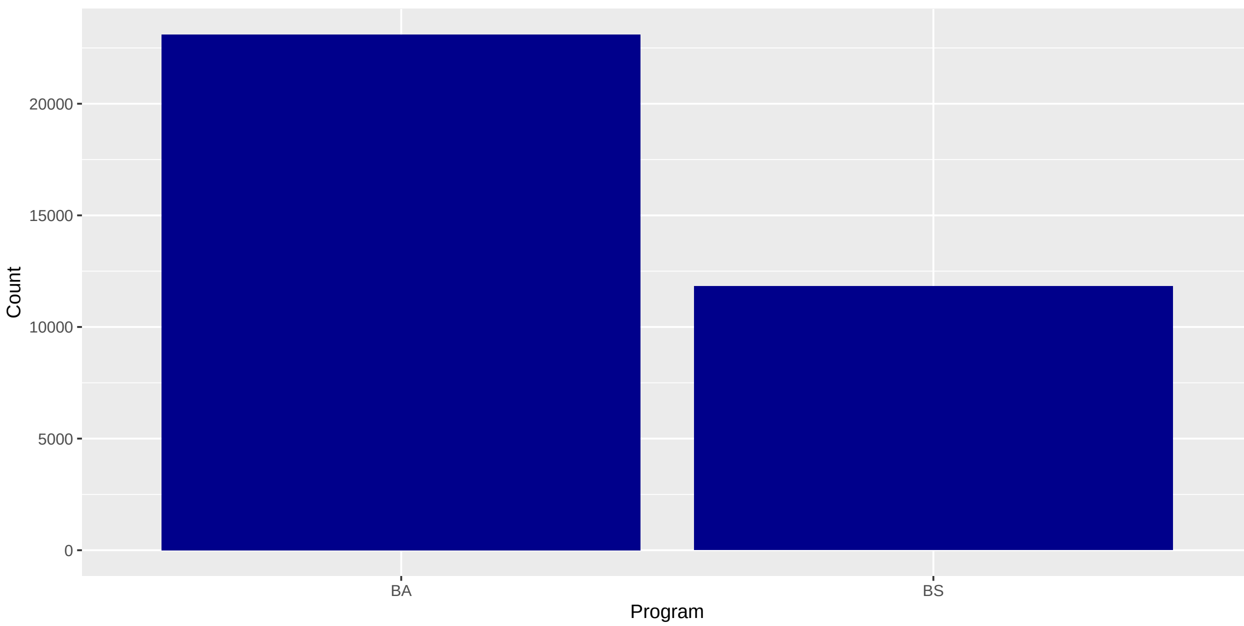
UG Campus - Frequency

```
freq(ug_desc_campus$prog, plain.ascii = TRUE, style = 'grid')
```

Frequencies
ug_desc_campus$prog
Type: Character

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
BA	23093	66.13	66.13	66.13	66.13
BS	11825	33.87	100.00	33.87	100.00
<NA>	0			0.00	100.00
Total	34918	100.00	100.00	100.00	100.00

```
ggplot(ug_desc_campus, aes(prog)) + xlab("Program") + ylab("Count") +
  geom_bar(fill = "darkblue")
```



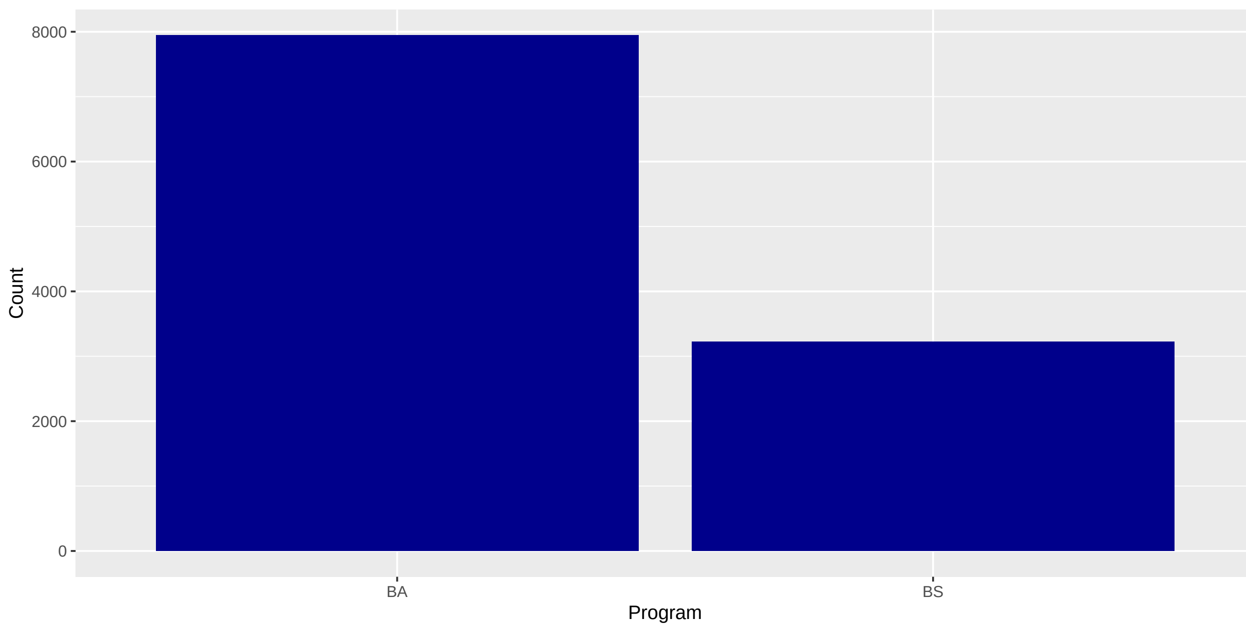
UG Online - Frequency

```
freq(ug_desc_online$prog, plain.ascii = TRUE, style = 'grid')
```

Frequencies
ug_desc_online$prog
Type: Character

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
BA	7943	71.12	71.12	71.12	71.12
BS	3226	28.88	100.00	28.88	100.00
<NA>	0			0.00	100.00
Total	11169	100.00	100.00	100.00	100.00

```r
ggplot(ug_desc_online, aes(prog)) + xlab("Program") + ylab("Count") +
  geom_bar(fill = "darkblue")
```



College/Unit

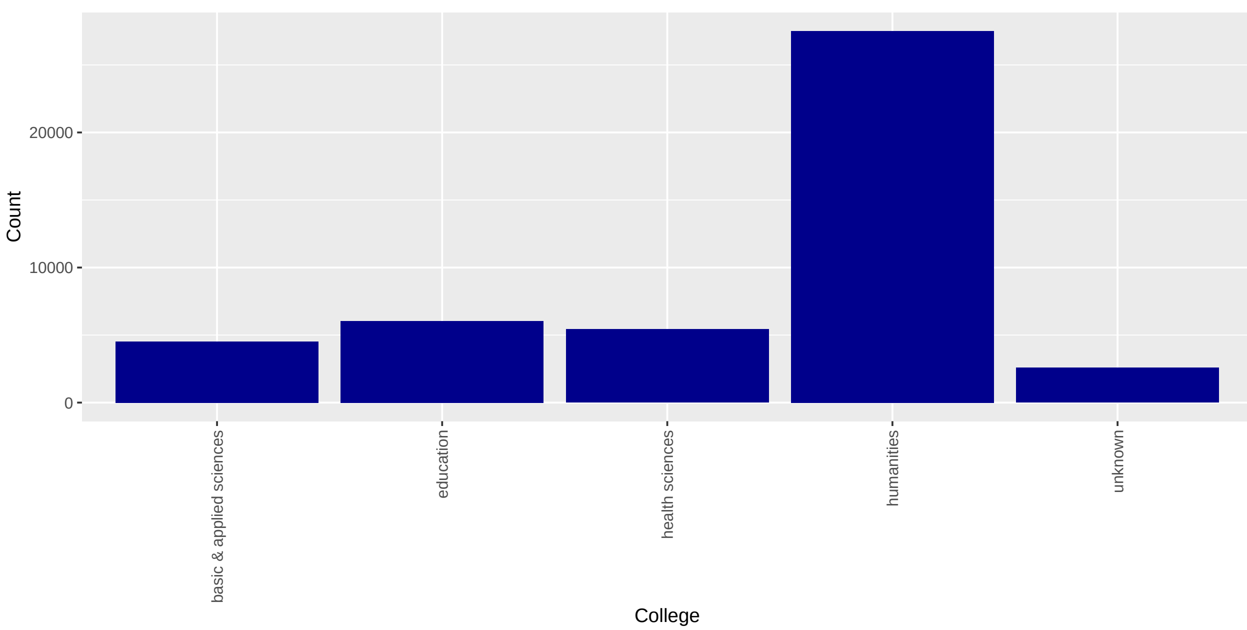
UG Dataset - Frequency

```
freq(ug_desc_all$coll, plain.ascii = TRUE, style = 'grid')
```

Frequencies
ug_desc_all$coll
Type: Character

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
basic & applied sciences	4519	9.81	9.81	9.81	9.81
education	6044	13.11	22.92	13.11	22.92
health sciences	5435	11.79	34.71	11.79	34.71
humanities	27507	59.68	94.40	59.68	94.40
unknown	2582	5.60	100.00	5.60	100.00
<NA>	0			0.00	100.00
Total	46087	100.00	100.00	100.00	100.00

```
ggplot(ug_desc_all, aes(coll)) +
  xlab("College") + ylab("Count") + geom_bar(fill = "darkblue") +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))
```



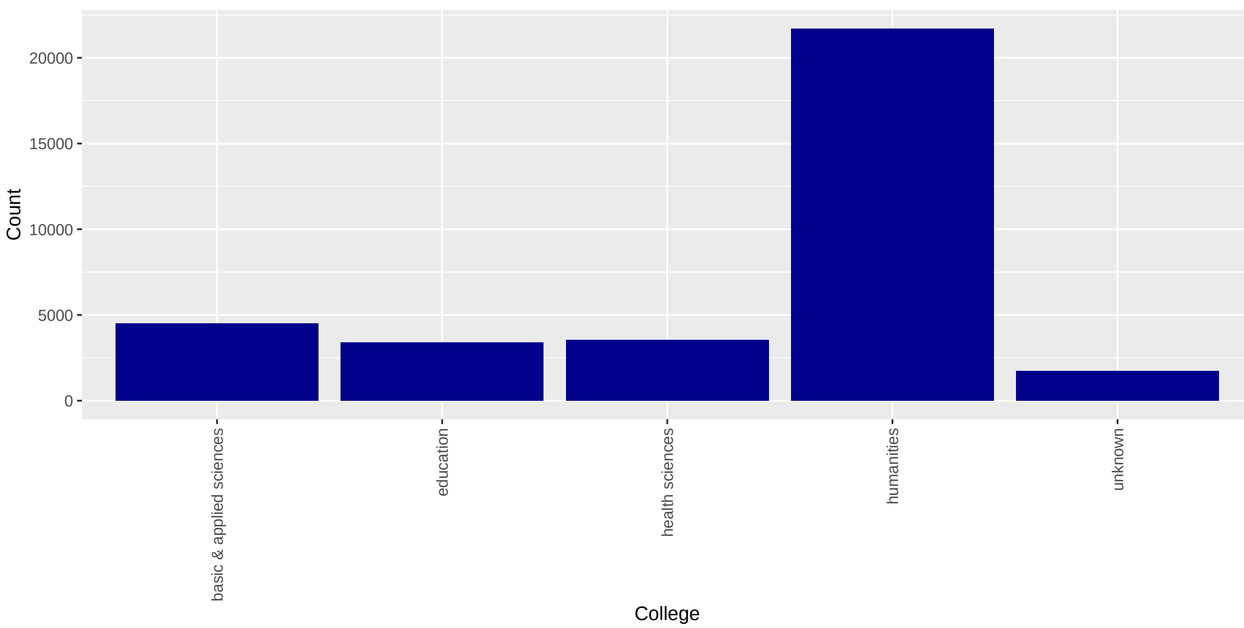
UG Campus - Frequency

```
freq(ug_desc_campus$coll, plain.ascii = TRUE, style = 'grid')
```

Frequencies
ug_desc_campus$coll
Type: Character

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
basic & applied sciences	4518	12.94	12.94	12.94	12.94
education	3401	9.74	22.68	9.74	22.68
health sciences	3559	10.19	32.87	10.19	32.87
humanities	21689	62.11	94.99	62.11	94.99
unknown	1751	5.01	100.00	5.01	100.00
<NA>	0			0.00	100.00
Total	34918	100.00	100.00	100.00	100.00

```
ggplot(ug_desc_campus, aes(coll)) + xlab("College") + ylab("Count") +
  geom_bar(fill = "darkblue") +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))
```



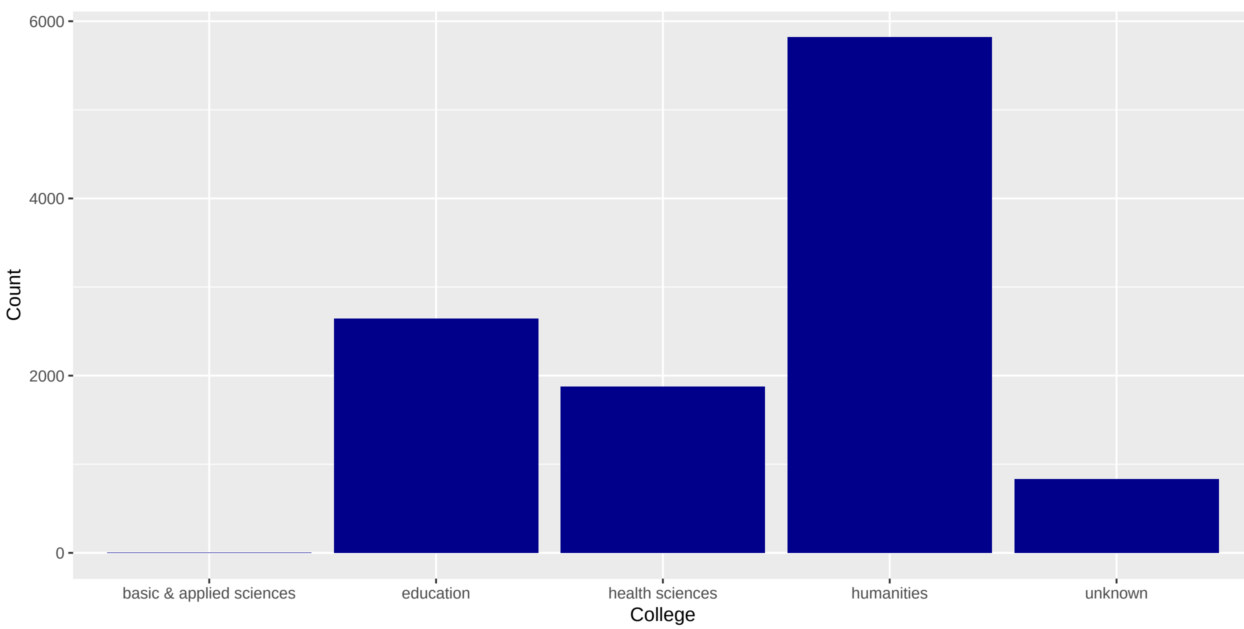
UG Online - Frequency

```r
freq(ug_desc_online$coll, plain.ascii = TRUE, style = 'grid')
```

Frequencies
ug_desc_online$coll
Type: Character

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
basic & applied sciences	1	0.009	0.009	0.009	0.009
education	2643	23.664	23.673	23.664	23.673
health sciences	1876	16.796	40.469	16.796	40.469
humanities	5818	52.091	92.560	52.091	92.560
unknown	831	7.440	100.000	7.440	100.000
<NA>	0			0.000	100.000
Total	11169	100.000	100.000	100.000	100.000

```r
ggplot(ug_desc_online, aes(coll)) + xlab("College") + ylab("Count") +
  geom_bar(fill = "darkblue")
```



Region

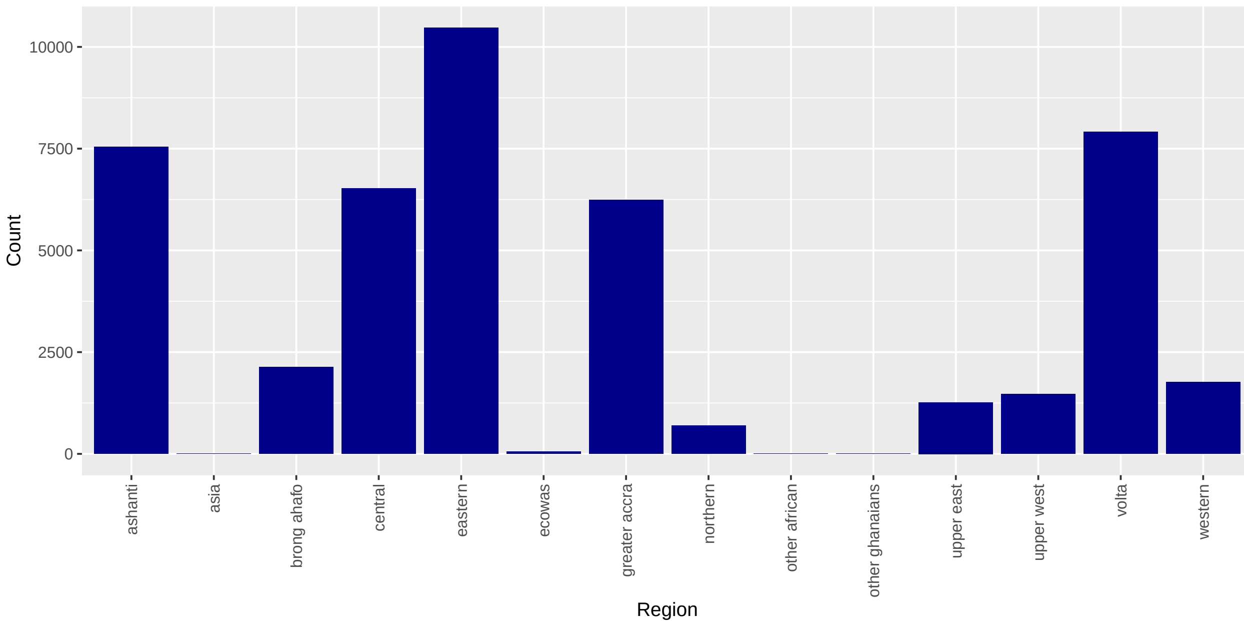
UG Dataset - Frequency

```
freq(ug_desc_all$reg, plain.ascii = TRUE, style = 'grid')
```

Frequencies
ug_desc_all$reg
Type: Character

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
ashanti	7547	16.3756	16.3756	16.3756	16.3756
asia	3	0.0065	16.3821	0.0065	16.3821
brong ahafo	2139	4.6412	21.0233	4.6412	21.0233
central	6519	14.1450	35.1683	14.1450	35.1683
eastern	10473	22.7244	57.8927	22.7244	57.8927
ecowas	60	0.1302	58.0229	0.1302	58.0229
greater accra	6236	13.5309	71.5538	13.5309	71.5538
northern	691	1.4993	73.0531	1.4993	73.0531
other african	3	0.0065	73.0596	0.0065	73.0596
other ghanaians	3	0.0065	73.0662	0.0065	73.0662
upper east	1267	2.7491	75.8153	2.7491	75.8153
upper west	1474	3.1983	79.0136	3.1983	79.0136
volta	7908	17.1589	96.1725	17.1589	96.1725
western	1764	3.8275	100.0000	3.8275	100.0000
<NA>	0			0.0000	100.0000
Total	46087	100.0000	100.0000	100.0000	100.0000

```
ggplot(ug_desc_all, aes(reg)) + xlab("Region") + ylab("Count") +
  geom_bar(fill = "darkblue") +
   theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))
```



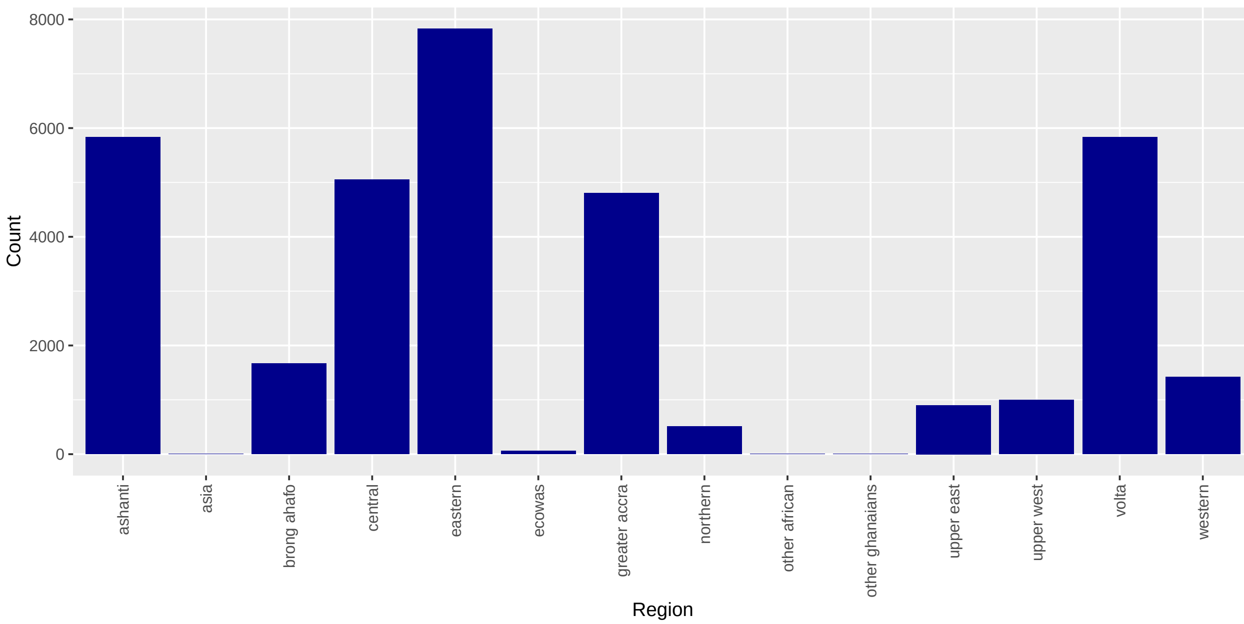
UG Campus - Frequency

```
freq(ug_desc_campus$reg, plain.ascii = TRUE, style = 'grid')
```

Frequencies
ug_desc_campus$reg
Type: Character

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
ashanti	5835	16.7106	16.7106	16.7106	16.7106
asia	3	0.0086	16.7192	0.0086	16.7192
brong ahafo	1671	4.7855	21.5047	4.7855	21.5047
central	5049	14.4596	35.9643	14.4596	35.9643
eastern	7830	22.4240	58.3882	22.4240	58.3882
ecowas	60	0.1718	58.5601	0.1718	58.5601
greater accra	4804	13.7579	72.3180	13.7579	72.3180
northern	509	1.4577	73.7757	1.4577	73.7757
other african	3	0.0086	73.7843	0.0086	73.7843
other ghanaians	3	0.0086	73.7929	0.0086	73.7929
upper east	902	2.5832	76.3761	2.5832	76.3761
upper west	999	2.8610	79.2371	2.8610	79.2371
volta	5832	16.7020	95.9391	16.7020	95.9391
western	1418	4.0609	100.0000	4.0609	100.0000
<NA>	0			0.0000	100.0000
Total	34918	100.0000	100.0000	100.0000	100.0000

```
ggplot(ug_desc_campus, aes(reg)) + xlab("Region") + ylab("Count") +
  geom_bar(fill = "darkblue") +
   theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))
```



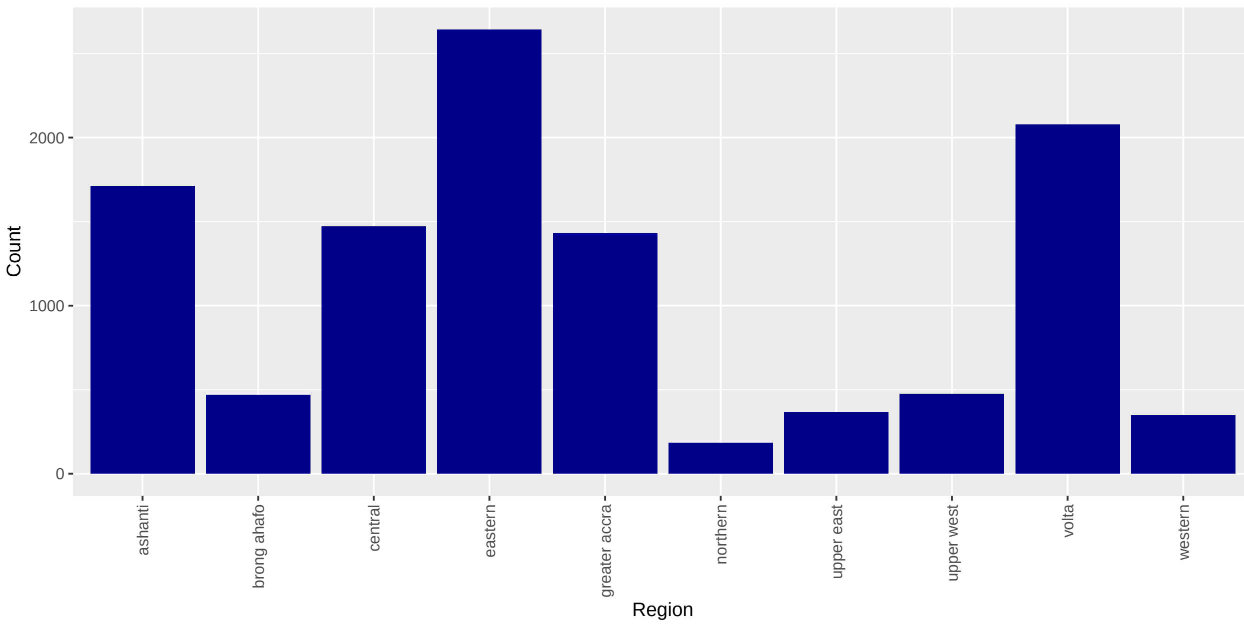
UG Online - Frequency

```
freq(ug_desc_online$reg, plain.ascii = TRUE, style = 'grid')
```

Frequencies
ug_desc_online$reg
Type: Character

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
ashanti	1712	15.33	15.33	15.33	15.33
brong ahafo	468	4.19	19.52	4.19	19.52
central	1470	13.16	32.68	13.16	32.68
eastern	2643	23.66	56.34	23.66	56.34
greater accra	1432	12.82	69.16	12.82	69.16
northern	182	1.63	70.79	1.63	70.79
upper east	365	3.27	74.06	3.27	74.06
upper west	475	4.25	78.31	4.25	78.31
volta	2076	18.59	96.90	18.59	96.90
western	346	3.10	100.00	3.10	100.00
<NA>	0			0.00	100.00
Total	11169	100.00	100.00	100.00	100.00

```
ggplot(ug_desc_online, aes(reg)) + xlab("Region") + ylab("Count") +
  geom_bar(fill = "darkblue") +
   theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))
```

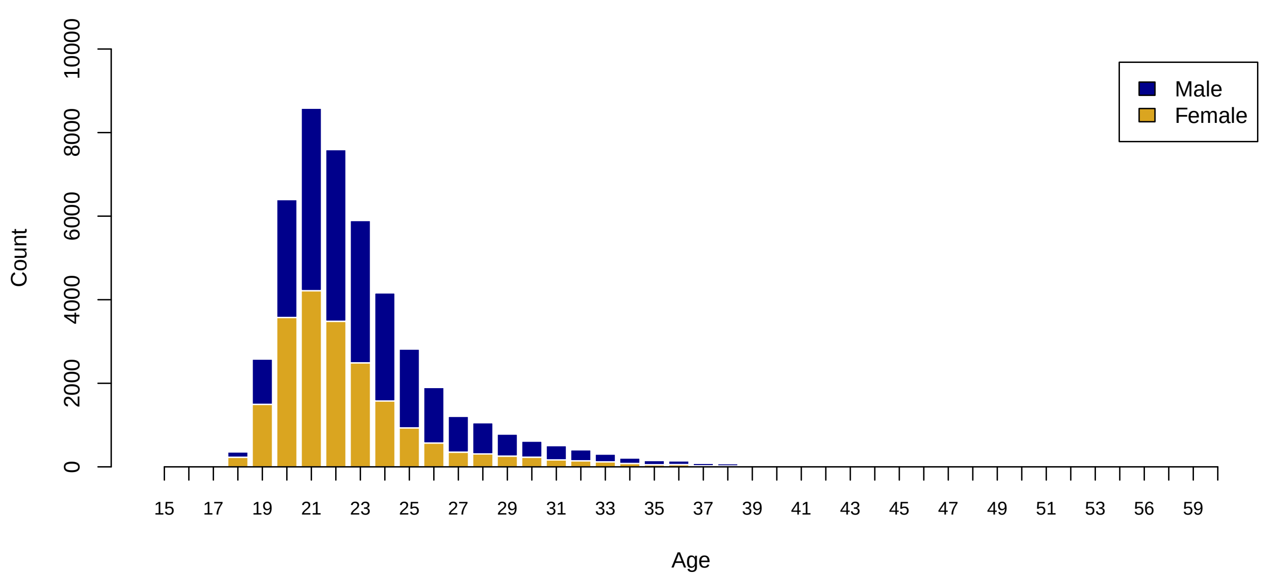


Gender-based Descriptive Statistics

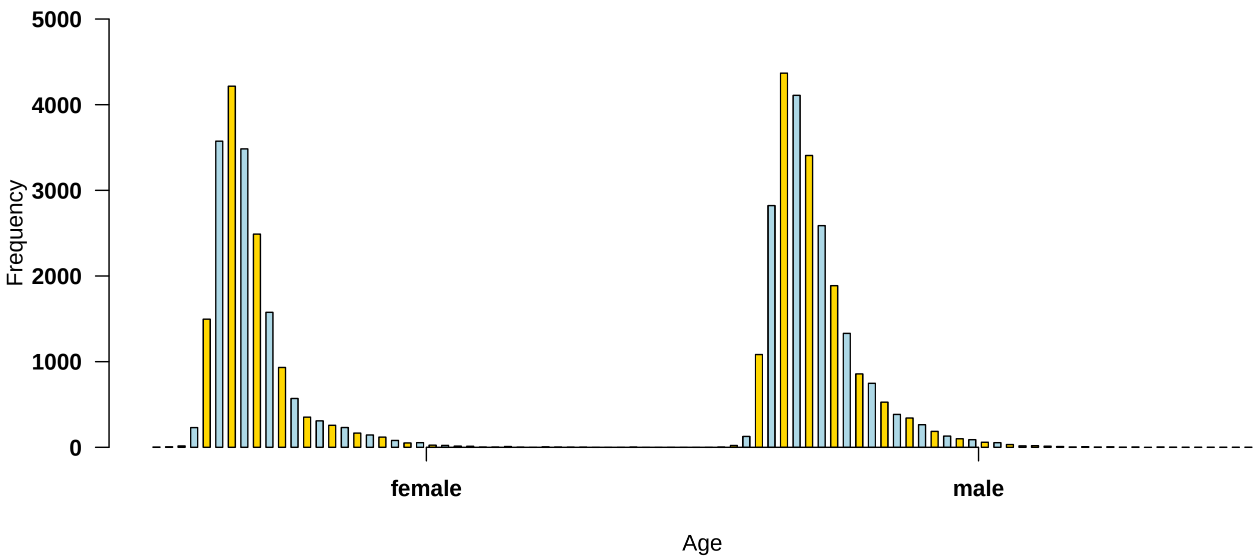
Gender Analysis

Gender distribution by age

```
aau_gender_threeway <- xtabs(~gender + age, data=ug_desc_gender)
aau_gender_threeway_ftable <-ftable(aau_gender_threeway)

barplot(aau_gender_threeway,
        xlab = "Age", ylab= "Count",
        border = "white", col = c("goldenrod", "darkblue"),
        cex.names = 0.8, ylim = c(0, 10000),
        axis.lty = 1, legend = (c("Female", "Male"))
)
```



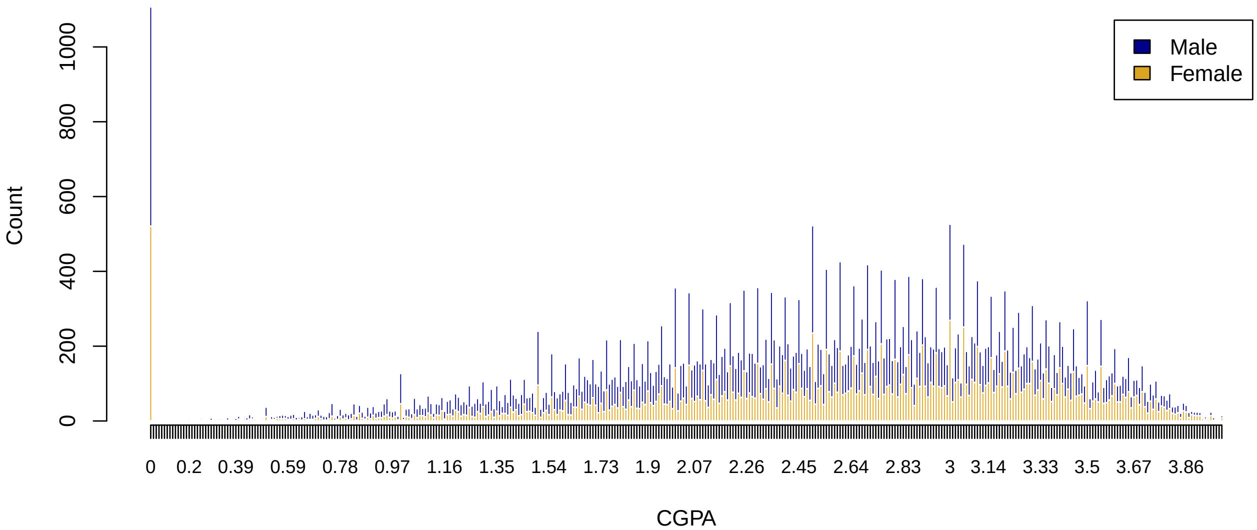
```
#table(ug_desc_gender$age, ug_desc_gender$gender)
barplot(table(ug_desc_gender$age, ug_desc_gender$gender), beside = TRUE,
        ylim = c(0, 5000), axis.lty = 1,
         las = 1, col = c("gold", "lightblue"), font.axis = 2,
        cex.name = 1, space = c(0.8, 0.8),
        xlab = "Age", ylab = "Frequency",
         legend.text = FALSE)
```



Online learning

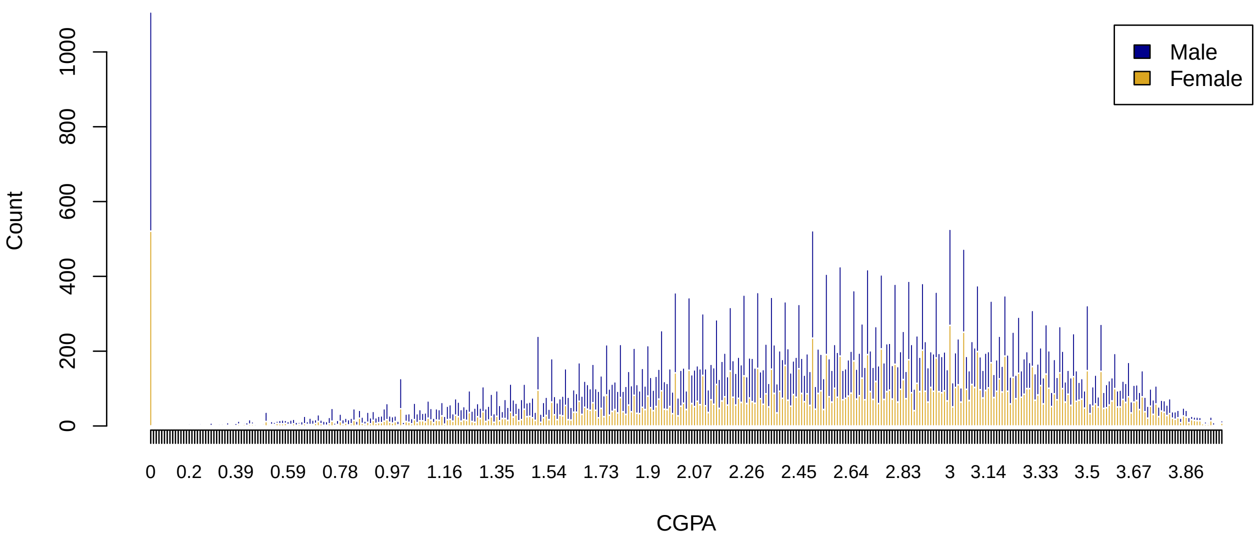
*Gender distribution by CGPA

```
aau_gender_threeway <- xtabs(~gender + cgpa, data=ug_desc_gender)
aau_gender_threeway_ftable <-ftable(aau_gender_threeway)

barplot(aau_gender_threeway,
        xlab = "CGPA", ylab= "Count",
        border = "white", col = c("goldenrod", "darkblue"),
        cex.names = 0.8,
        axis.lty = 1, legend = (c("Female", "Male"))
)
```



***Gender distribution by CGPA**

```
ug_gender_threeway <- xtabs(~gender + cgpa, data=ug_desc_gender)
ug_gender_threeway_ftable <-ftable(ug_gender_threeway)

barplot(ug_gender_threeway,
        xlab = "CGPA", ylab= "Count",
        border = "white", col = c("goldenrod", "darkblue"),
        cex.names = 0.8,
        axis.lty = 1, legend = (c("Female", "Male"))
)
```



***

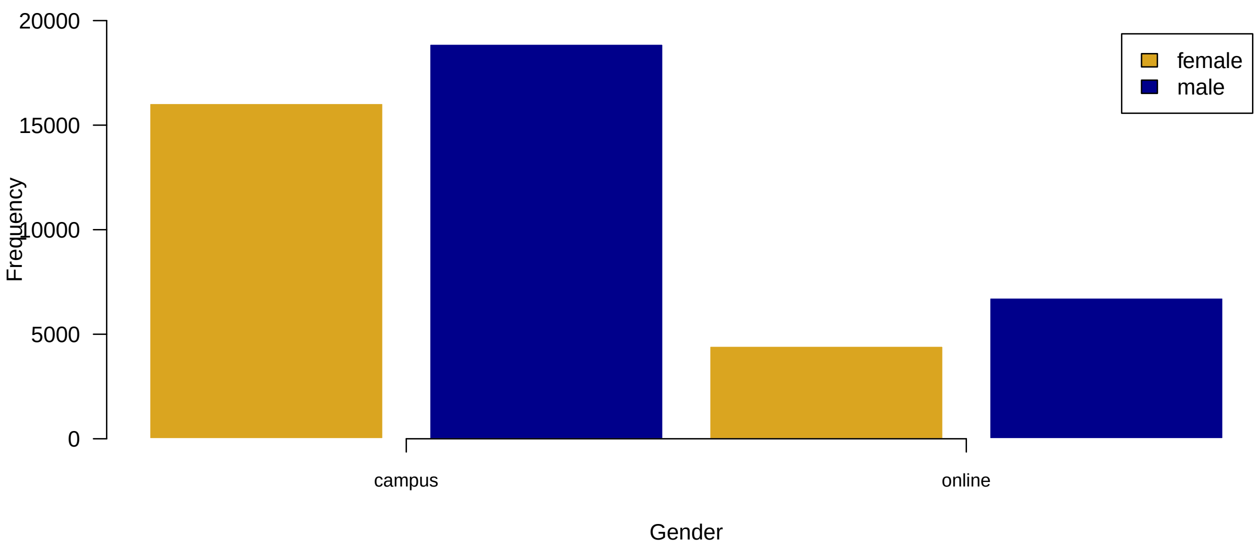
Gender distribution by modality

```
table(ug_desc_gender$gender, ug_desc_gender$modality)
```

```
     campus online
```

female 16041 4431 male 18877 6738

```
barplot(table(ug_desc_gender$gender, ug_desc_gender$modality), beside = TRUE,
        ylim = c(0, 20000), axis.lty = 1,
        las = 1, col = c("goldenrod", "darkblue"), border= "white",
        cex.name = 0.8, space = c(0.2, 0.2),
        xlab = "Gender", ylab = "Frequency", legend.text = TRUE)
```



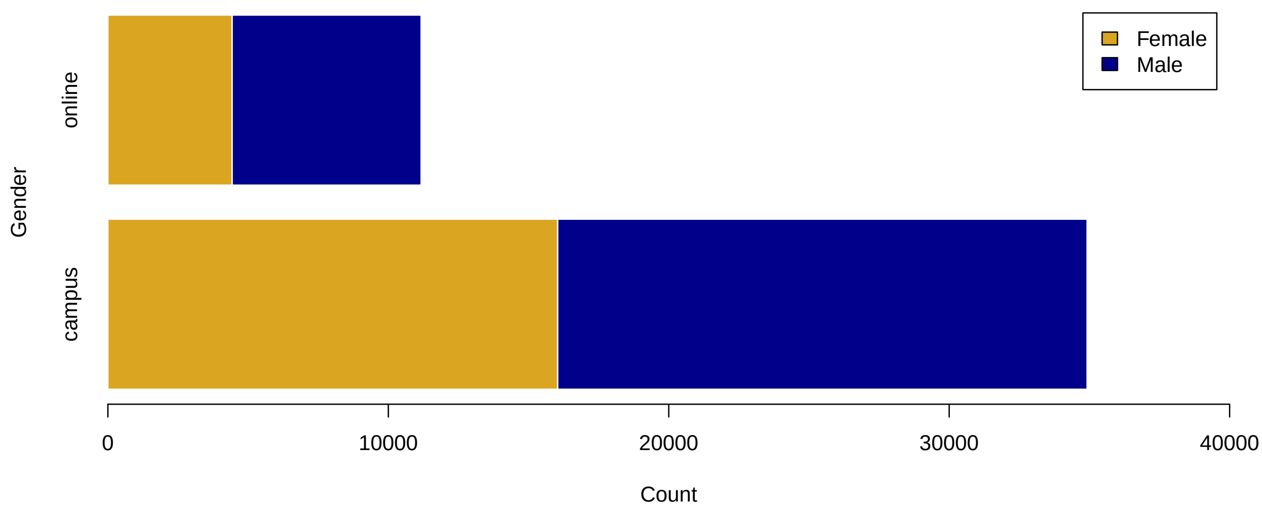
```
table(ug_desc_gender$gender, ug_desc_gender$modality)
```

```
     campus online
```

female 16041 4431 male 18877 6738

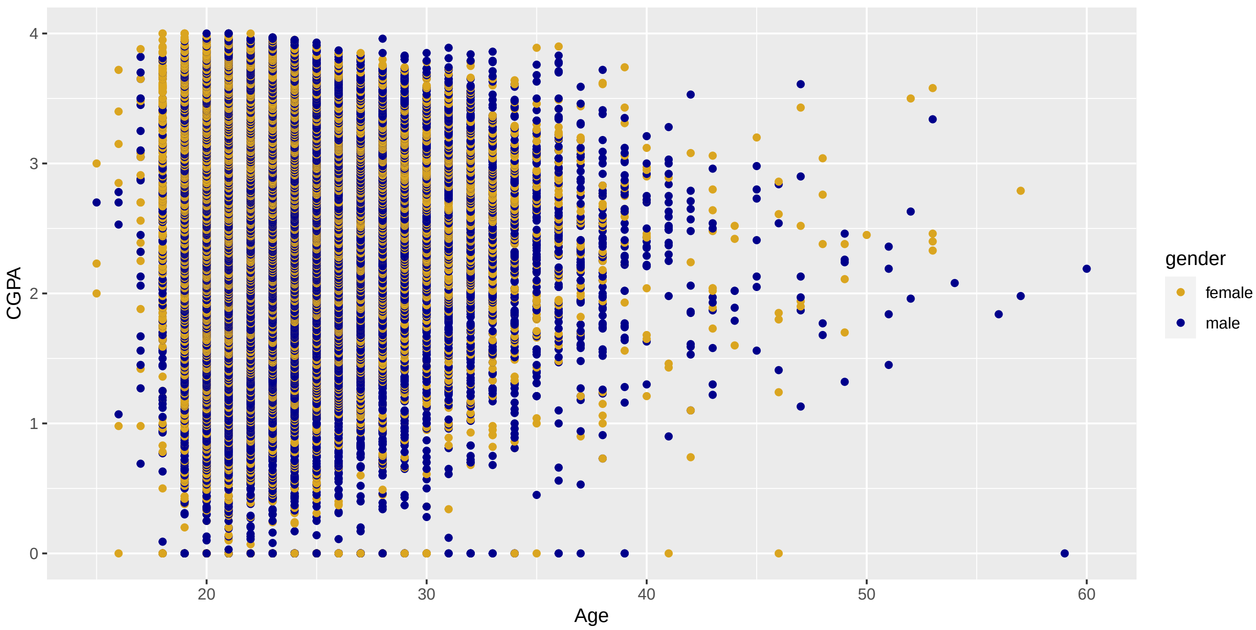
```
ug_gender_threeway <- xtabs(~gender + modality, data=ug_desc_gender)
ug_gender_threeway_ftable <-ftable(ug_gender_threeway)

barplot(ug_gender_threeway,
        xlab = "Count",
        ylab= "Gender",
        horiz = TRUE,
```

```
        col = c("goldenrod", "darkblue"),
        border = "white", xlim = c(0, 40000),
        legend = (c("Female", "Male"))
)
```



Gender distribution by age and CGPA

```
ggplot(ug_desc_gender, aes(x = age, y = cgpa, color = gender)) +
  geom_point() +
  labs(x = "Age", y = "CGPA") +
  scale_color_manual(values = c("goldenrod", "darkblue"))
```



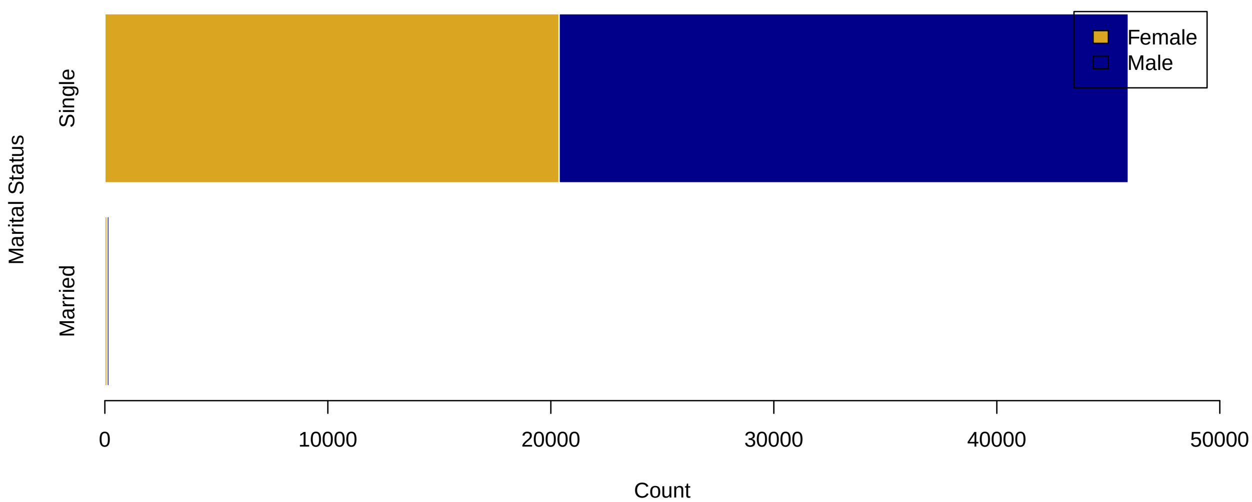
*Gender distribution by marital status

```
table(ug_desc_gender$gender, ug_desc_gender$ms)
```

```
     Married Single
```

female 101 20371 male 89 25526

```
ug_gender_threeway <- xtabs(~gender + ms, data=ug_desc_gender)
ug_gender_threeway_ftable <-ftable(ug_gender_threeway)

barplot(ug_gender_threeway,
        xlab = "Count",
        ylab= "Marital Status",
        horiz = TRUE, density = NULL,
        col = c("goldenrod", "darkblue"),
        border = "white", xlim = c(0, 50000),
        legend = (c("Female", "Male"))
)
```



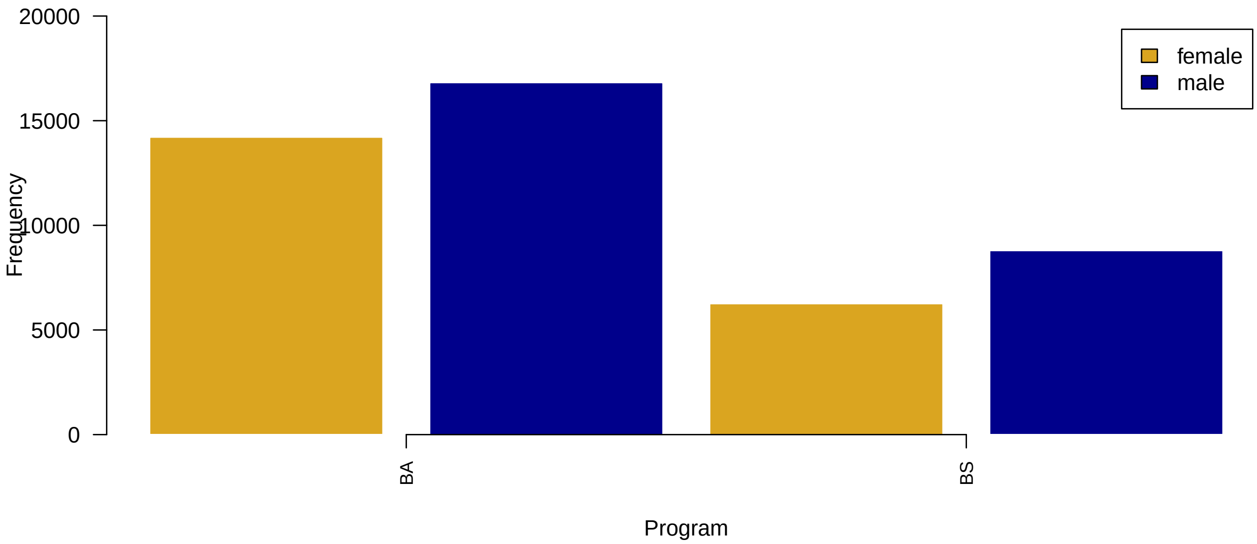
Gender distribution by degree program

```
table(ug_desc_gender$gender, ug_desc_gender$prog)
```

```
        BA    BS
```

female 14215 6257 male 16821 8794

```
barplot(table(ug_desc_gender$gender, ug_desc_gender$prog), beside = TRUE,
        ylim = c(0, 20000), axis.lty = 1,
        las = 1, col = c("goldenrod", "darkblue"), border= "white",
        cex.name = 0.8, space = c(0.2, 0.2),
        xlab = "Program", ylab = "Frequency", las = 2, legend.text = TRUE)
```

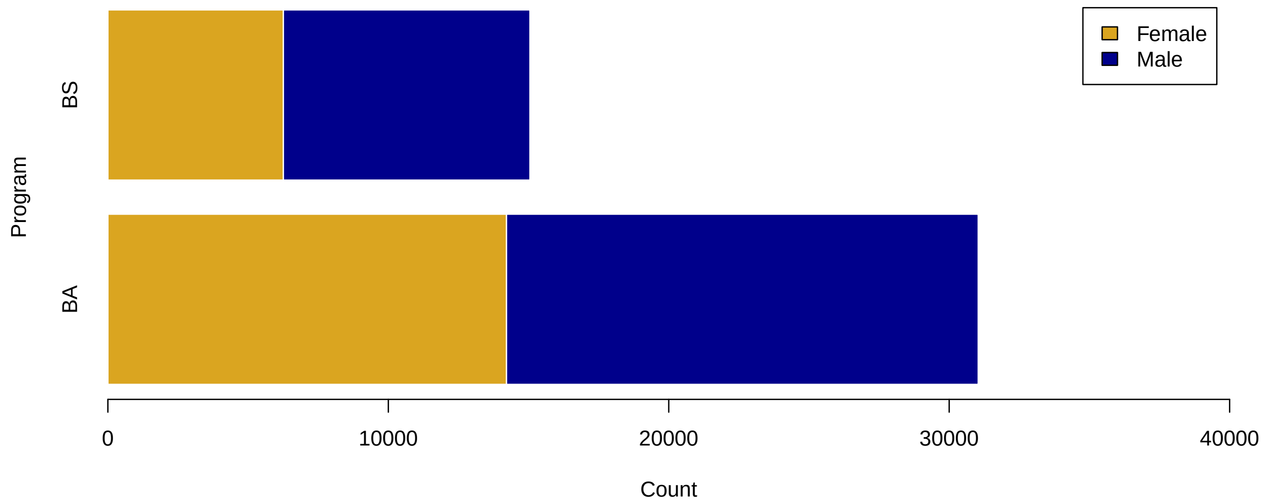


```
table(ug_desc_gender$gender, ug_desc_gender$prog)
```

```
        BA    BS
```

female 14215 6257 male 16821 8794

```
ug_gender_threeway <- xtabs(~gender + prog, data=ug_desc_gender)
ug_gender_threeway_ftable <-ftable(ug_gender_threeway)

barplot(ug_gender_threeway,
        xlab = "Count",
        ylab= "Program",
        horiz = TRUE,
        col = c("goldenrod", "darkblue"),
        border = "white", xlim = c(0, 40000),
        legend = (c("Female", "Male"))
)
```


Female
Male
BS
BA
Program
0
10000
20000
30000
40000
Count

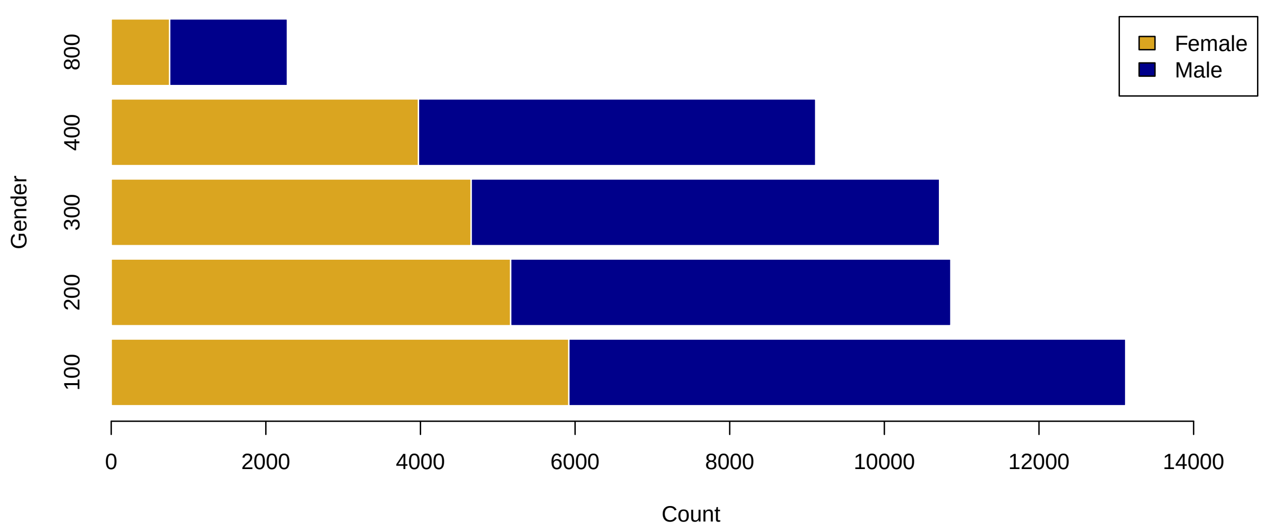
Gender distribution by year (level)

```
table(ug_desc_gender$gender, ug_desc_gender$Level)
```

```
      100  200  300  400  800
```

female 5919 5167 4656 3974 756 male 7203 5693 6058 5138 1523

```
ug_gender_threeway <- xtabs(~gender + Level, data=ug_desc_gender)
ug_gender_threeway_ftable <-ftable(ug_gender_threeway)

barplot(ug_gender_threeway,
        xlab = "Count",
        ylab= "Gender",
        horiz = TRUE,
        col = c("goldenrod", "darkblue"),
        border = "white", xlim = c(0, 15000),
        legend = (c("Female", "Male"))
)
```



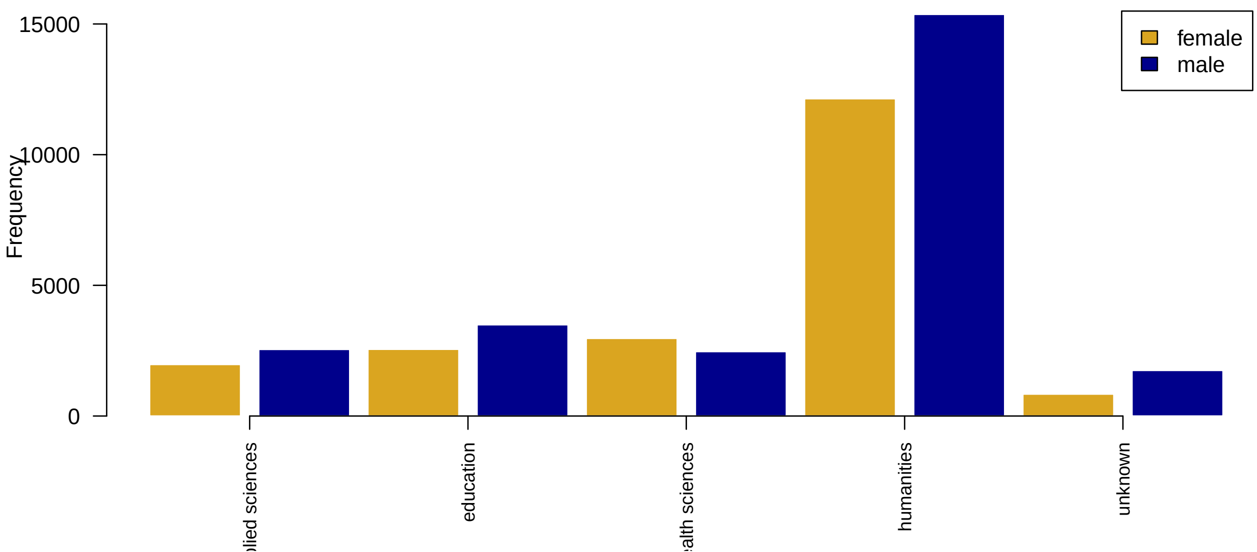
Gender distribution by college

```
table(ug_desc_gender$gender, ug_desc_gender$coll)
```

```
     basic & applied sciences education health sciences humanities unknown
```

female 1971 2553 2970 12140 838 male 2548 3491 2465 15367 1744

```
barplot(table(ug_desc_gender$gender, ug_desc_gender$coll), beside = TRUE,
        ylim = c(0, 16000), axis.lty = 1,
        las = 1, col = c("goldenrod", "darkblue"), border= "white",
        cex.name = 0.8, space = c(0.2, 0.2),
        xlab = "", ylab = "Frequency", las = 2, legend.text = TRUE)
```



Gender distribution by region

```
table(ug_desc_gender$gender, ug_desc_gender$reg)
```

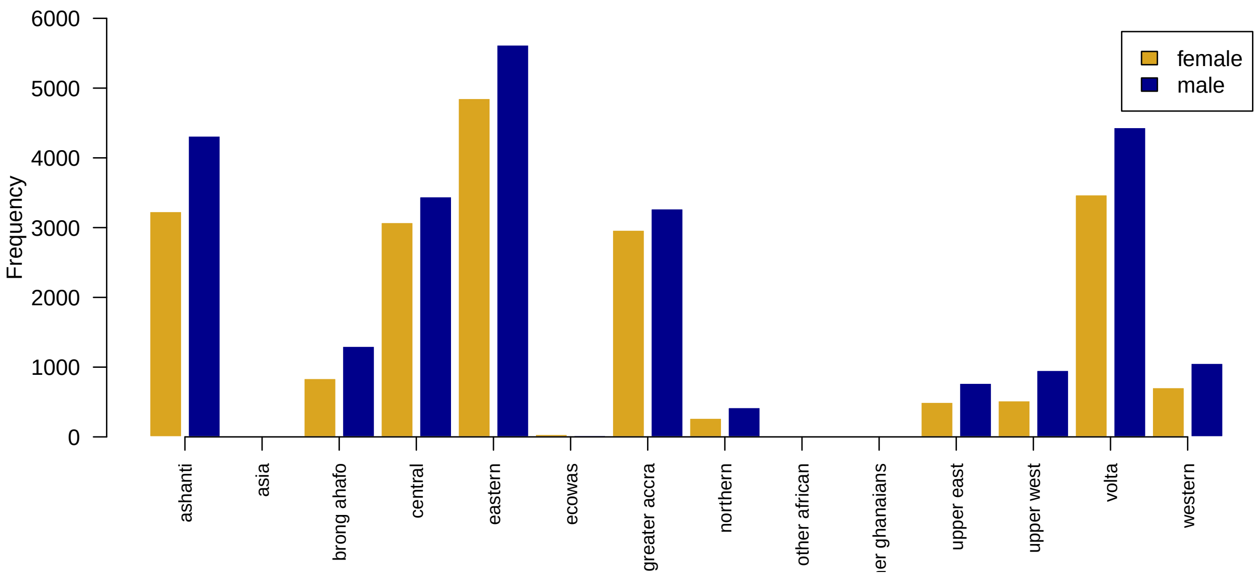
```
     ashanti asia brong ahafo central eastern ecowas greater accra northern
```

female 3232 2 839 3075 4853 37 2965 269 male 4315 1 1300 3444 5620 23 3271 422

```
     other african other ghanaians upper east upper west volta western
```

female 2 2 497 519 3472 708 male 1 1 770 955 4436 1056

```
barplot(table(ug_desc_gender$gender, ug_desc_gender$reg), beside = TRUE,
        ylim = c(0, 6000), axis.lty = 1,
        las = 1, col = c("goldenrod", "darkblue"), border= "white",
        cex.name = 0.8, space = c(0.2, 0.2),
        xlab = "", ylab = "Frequency", las = 2, legend.text = TRUE)
```



University of Ghana

Matching

Research Question

Is online instruction as effective as face-to-face instruction measured by Cumulative Grade Point Average (CGPA)?

Matching with MatchIt

Pre-matching balance assessment

```
#Logistic Regression with method set to NULL to assess balance before matching
ugm.out0 <- matchit(treat ~ cgpa + age + gender + ms + level + reg + coll + prog,
                    data = ug_match, method = NULL, distance = "glm")
summary(ugm.out0)
```

```
##
## Call:
## matchit(formula = treat ~ cgpa + age + gender + ms + level +
##     reg + coll + prog, data = ug_match, method = NULL, distance = "glm")
##
## Summary of Balance for All Data:
##                              Means Treated Means Control Std. Mean Diff.
## distance                            0.4557        0.1741          1.0908
## cgpa                                2.2849        2.6274         -0.5004
## age                                25.3589       22.2836          0.6519
## gender                              0.6033        0.5406          0.1281
## ms                                  0.9927        0.9969         -0.0487
## level                             269.1915      262.3232          0.0428
## regashanti                          0.1533        0.1671         -0.0384
## regasia                             0.0000        0.0001         -0.0106
## regbrong ahafo                      0.0419        0.0479         -0.0297
## regcentral                          0.1316        0.1446         -0.0384
## regeastern                          0.2366        0.2242          0.0292
## regecowas                           0.0000        0.0017         -0.0477
## reggreater accra                    0.1282        0.1376         -0.0280
## regnorthern                         0.0163        0.0146          0.0136
## regother african                    0.0000        0.0001         -0.0106
## regother ghanaians                  0.0000        0.0001         -0.0106
## regupper east                       0.0327        0.0258          0.0385
## regupper west                       0.0425        0.0286          0.0690
## regvolta                            0.1859        0.1670          0.0485
## regwestern                          0.0310        0.0406         -0.0556
```

```
## collbasic & applied sciences        0.0001        0.1294        -13.6654
## colleducation                       0.2366        0.0974          0.3276
## collhealth sciences                 0.1680        0.1019          0.1767
## collhumanities                      0.5209        0.6211         -0.2006
## collunknown                         0.0744        0.0501          0.0924
## progBA                              0.7112        0.6613          0.1099
## progBS                              0.2888        0.3387         -0.1099
##                              Var. Ratio eCDF Mean eCDF Max
## distance                         2.4295    0.3335   0.5177
## cgpa                             0.9257    0.0879   0.2180
## age                              3.1705    0.0699   0.3282
## gender                                .    0.0627   0.0627
## ms                                    .    0.0041   0.0041
## level                            0.9482    0.0165   0.0411
## regashanti                            .    0.0138   0.0138
## regasia                               .    0.0001   0.0001
## regbrong ahafo                        .    0.0060   0.0060
## regcentral                            .    0.0130   0.0130
## regeastern                            .    0.0124   0.0124
## regecowas                             .    0.0017   0.0017
## reggreater accra                      .    0.0094   0.0094
## regnorthern                           .    0.0017   0.0017
## regother african                      .    0.0001   0.0001
## regother ghanaians                    .    0.0001   0.0001
## regupper east                         .    0.0068   0.0068
## regupper west                         .    0.0139   0.0139
## regvolta                              .    0.0189   0.0189
## regwestern                            .    0.0096   0.0096
## collbasic & applied sciences          .    0.1293   0.1293
## colleducation                         .    0.1392   0.1392
## collhealth sciences                   .    0.0660   0.0660
## collhumanities                        .    0.1002   0.1002
## collunknown                           .    0.0243   0.0243
## progBA                                .    0.0498   0.0498
## progBS                                .    0.0498   0.0498
##
## Sample Sizes:
##           Control Treated
## All         34918   11169
## Matched     34918   11169
## Unmatched       0       0
## Discarded       0       0
```

Matching

```r
#Matching set to glm for generalized linear model for logistic regression

ugm.out1 <- matchit(treat ~ cgpa + age + gender + ms + level + reg + coll + prog,
                    data = ug_match,
                 method = "subclass", distance = "glm", link = "probit")
summary(ugm.out1)
```

```
##
## Call:
## matchit(formula = treat ~ cgpa + age + gender + ms + level +
##     reg + coll + prog, data = ug_match, method = "subclass",
##     distance = "glm", link = "probit")
##
## Summary of Balance for All Data:
##                               Means Treated Means Control Std. Mean Diff.
## distance                             0.4431        0.1734          1.1028
## cgpa                                 2.2849        2.6274         -0.5004
## age                                 25.3589       22.2836          0.6519
## gender                               0.6033        0.5406          0.1281
## ms                                   0.9927        0.9969         -0.0487
## level                              269.1915      262.3232          0.0428
## regashanti                           0.1533        0.1671         -0.0384
## regasia                              0.0000        0.0001         -0.0106
## regbrong ahafo                       0.0419        0.0479         -0.0297
## regcentral                           0.1316        0.1446         -0.0384
## regeastern                           0.2366        0.2242          0.0292
## regecowas                            0.0000        0.0017         -0.0477
## reggreater accra                     0.1282        0.1376         -0.0280
## regnorthern                          0.0163        0.0146          0.0136
## regother african                     0.0000        0.0001         -0.0106
## regother ghanaians                   0.0000        0.0001         -0.0106
## regupper east                        0.0327        0.0258          0.0385
## regupper west                        0.0425        0.0286          0.0690
## regvolta                             0.1859        0.1670          0.0485
## regwestern                           0.0310        0.0406         -0.0556
## collbasic & applied sciences         0.0001        0.1294        -13.6654
## colleducation                        0.2366        0.0974          0.3276
## collhealth sciences                  0.1680        0.1019          0.1767
## collhumanities                       0.5209        0.6211         -0.2006
## collunknown                          0.0744        0.0501          0.0924
## progBA                               0.7112        0.6613          0.1099
## progBS                               0.2888        0.3387         -0.1099
##                               Var. Ratio eCDF Mean eCDF Max
## distance                          2.2864    0.3334   0.5166
## cgpa                              0.9257    0.0879   0.2180
## age                               3.1705    0.0699   0.3282
## gender                                 .    0.0627   0.0627
## ms                                     .    0.0041   0.0041
## level                             0.9482    0.0165   0.0411
## regashanti                             .    0.0138   0.0138
## regasia                                .    0.0001   0.0001
```

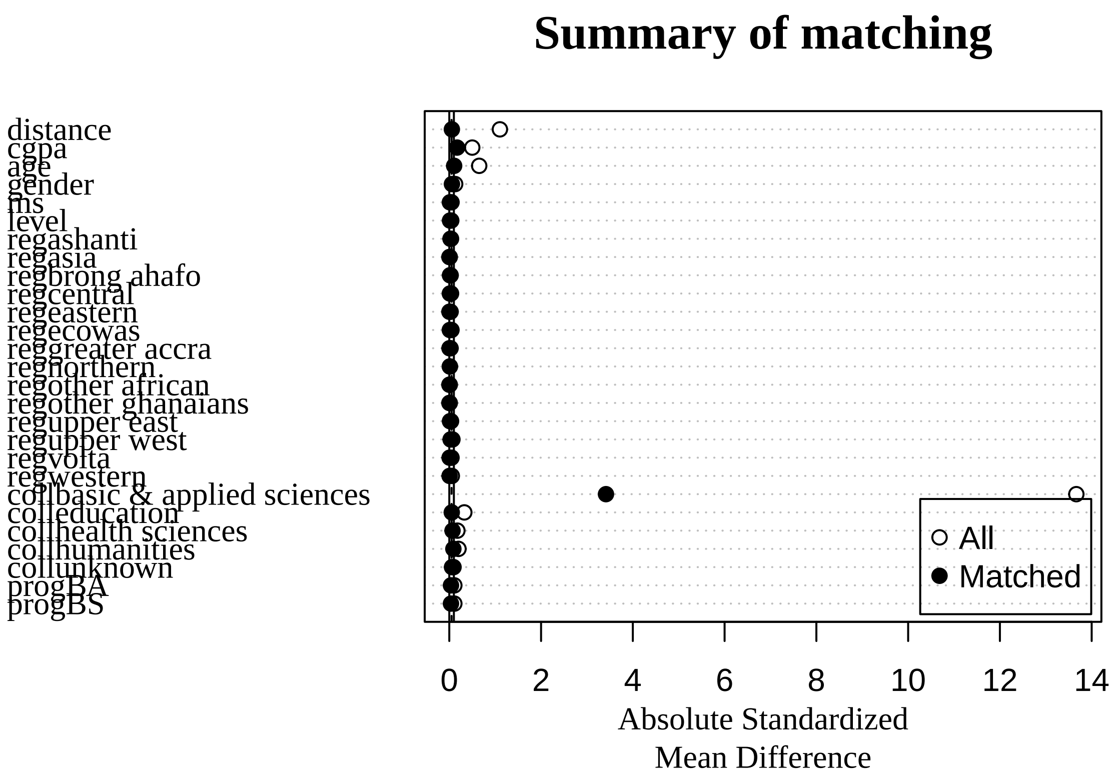
```
## regbrong ahafo                          .    0.0060   0.0060
## regcentral                              .    0.0130   0.0130
## regeastern                              .    0.0124   0.0124
## regecowas                               .    0.0017   0.0017
## reggreater accra                        .    0.0094   0.0094
## regnorthern                             .    0.0017   0.0017
## regother african                        .    0.0001   0.0001
## regother ghanaians                      .    0.0001   0.0001
## regupper east                           .    0.0068   0.0068
## regupper west                           .    0.0139   0.0139
## regvolta                                .    0.0189   0.0189
## regwestern                              .    0.0096   0.0096
## collbasic & applied sciences            .    0.1293   0.1293
## colleducation                           .    0.1392   0.1392
## collhealth sciences                     .    0.0660   0.0660
## collhumanities                          .    0.1002   0.1002
## collunknown                             .    0.0243   0.0243
## progBA                                  .    0.0498   0.0498
## progBS                                  .    0.0498   0.0498
##
## Summary of Balance Across Subclasses
##                              Means Treated Means Control Std. Mean Diff.
## distance                            0.4431        0.4293          0.0567
## cgpa                                2.2849        2.1682          0.1705
## age                                25.3589       24.8584          0.1061
## gender                              0.6033        0.6315         -0.0576
## ms                                  0.9927        0.9938         -0.0129
## level                             269.1915      266.6431          0.0159
## regashanti                          0.1533        0.1627         -0.0261
## regasia                             0.0000        0.0000         -0.0027
## regbrong ahafo                      0.0419        0.0449         -0.0150
## regcentral                          0.1316        0.1274          0.0125
## regeastern                          0.2366        0.2380         -0.0032
## regecowas                           0.0000        0.0004         -0.0119
## reggreater accra                    0.1282        0.1297         -0.0046
## regnorthern                         0.0163        0.0146          0.0130
## regother african                    0.0000        0.0000         -0.0027
## regother ghanaians                  0.0000        0.0000         -0.0027
## regupper east                       0.0327        0.0300          0.0151
## regupper west                       0.0425        0.0369          0.0277
## regvolta                            0.1859        0.1831          0.0071
## regwestern                          0.0310        0.0321         -0.0063
## collbasic & applied sciences        0.0001        0.0324         -3.4150
## colleducation                       0.2366        0.2597         -0.0542
## collhealth sciences                 0.1680        0.1416          0.0705
## collhumanities                      0.5209        0.4764          0.0891
## collunknown                         0.0744        0.0899         -0.0591
## progBA                              0.7112        0.6945          0.0368
## progBS                              0.2888        0.3055         -0.0368
##                              Var. Ratio eCDF Mean eCDF Max
## distance                         0.9311    0.0247   0.0608
## cgpa                             0.7435    0.0336   0.0775
## age                              0.8915    0.0183   0.1024
## gender                                .    0.0282   0.0282
```

```
## ms                                    .     0.0011    0.0011
## level                            0.9420     0.0113    0.0235
## regashanti                            .     0.0094    0.0094
## regasia                               .     0.0000    0.0000
## regbrong ahafo                        .     0.0030    0.0030
## regcentral                            .     0.0042    0.0042
## regeastern                            .     0.0014    0.0014
## regecowas                             .     0.0004    0.0004
## reggreater accra                      .     0.0015    0.0015
## regnorthern                           .     0.0016    0.0016
## regother african                      .     0.0000    0.0000
## regother ghanaians                    .     0.0000    0.0000
## regupper east                         .     0.0027    0.0027
## regupper west                         .     0.0056    0.0056
## regvolta                              .     0.0028    0.0028
## regwestern                            .     0.0011    0.0011
## collbasic & applied sciences          .     0.0323    0.0323
## colleducation                         .     0.0231    0.0231
## collhealth sciences                   .     0.0264    0.0264
## collhumanities                        .     0.0445    0.0445
## collunknown                           .     0.0155    0.0155
## progBA                                .     0.0167    0.0167
## progBS                                .     0.0167    0.0167
##
## Sample Sizes:
##                 Control Treated
## All           34918.     11169
## Matched (ESS)  8402.42   11169
## Matched       34918.     11169
## Unmatched         0.         0
## Discarded         0.         0
```

```
ugm.data <- match.data(ugm.out1)
```

Summary of matching

```
#Summary of matching
plot(summary(ugm.out1), main = "Summary of matching", sub = "",
     family = "Times",
     cex.main = 1.5,
     cex.sub = 1,
     cex.lab = 1,
     cex.axis = 1,
     pch  = 16,
     col.main = "black",
     col.sub = "black",
     col.lab = "black",
     col.axis = "black")
```

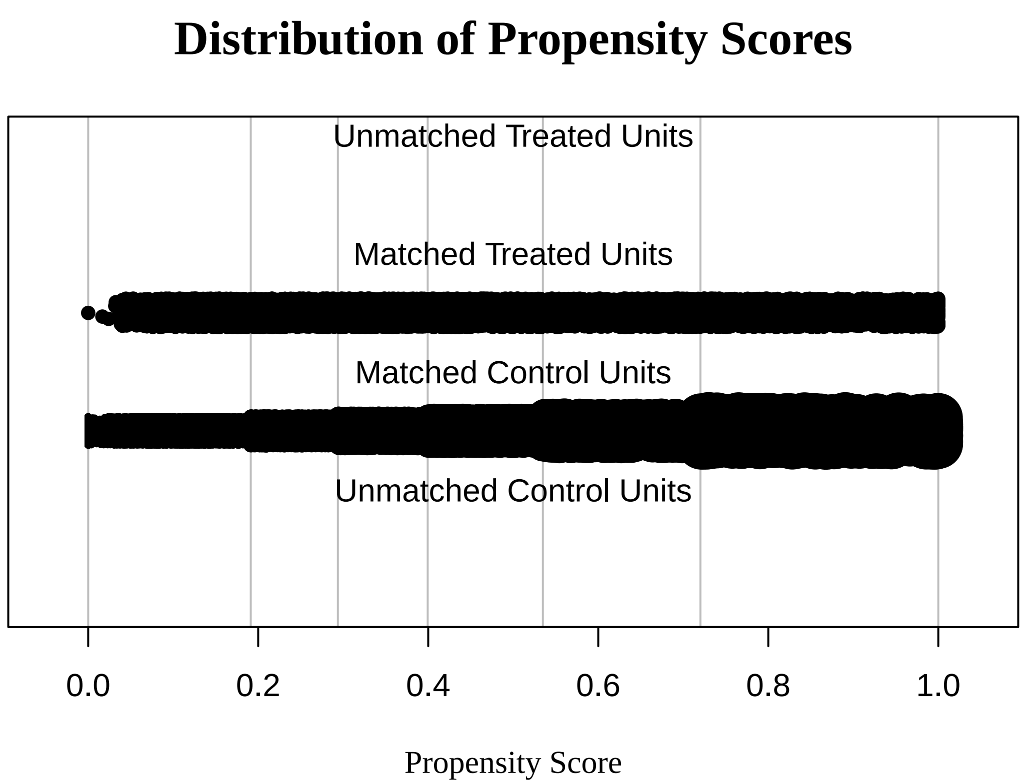


Summary of matching
distance
cgpa
age
gender
ms
level
regashanti
regasia
regbrong ahafo
regcentral
regeastern
regecowas
reggreater accra
regnorthern.
regother african
regother ghanaians
regupper east
regupper west
regvolta
regwestern
collbasic & applied sciences
colleducation
collhealth sciences
collhumanities
collunknown
progBA
progBS
All
Matched
0
2
4
6
8
10
12
14
Absolute Standardized
Mean Difference

Checking balance

Distribution of propensity scores

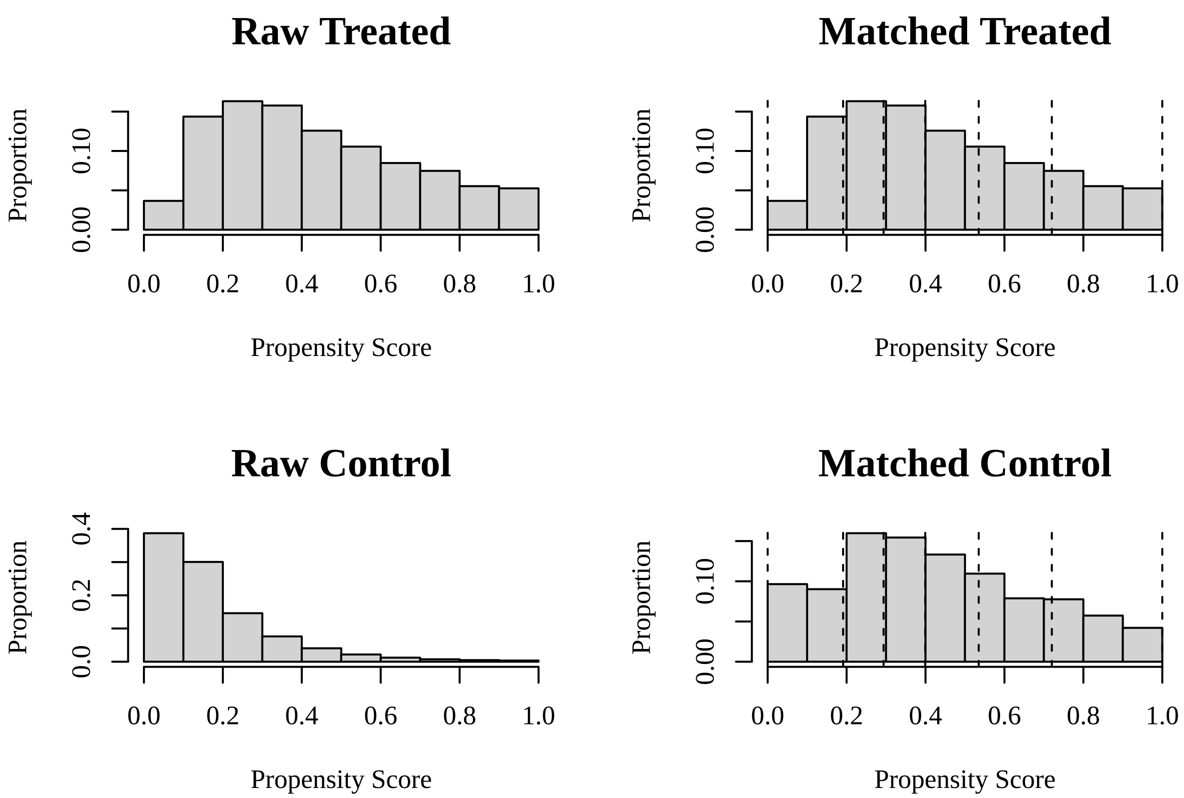
```
plot(ugm.out1, type = "jitter", interactive = FALSE,
     family = "Times",
     cex.main = 1.5,
     cex.sub = 1,
     cex.lab = 1,
     cex.axis = 1,
     pch  = 16,
     col.main = "black",
     col.sub = "black",
     col.lab = "black",
     col.axis = "black")
```



Histogram - Comparison of raw and treated

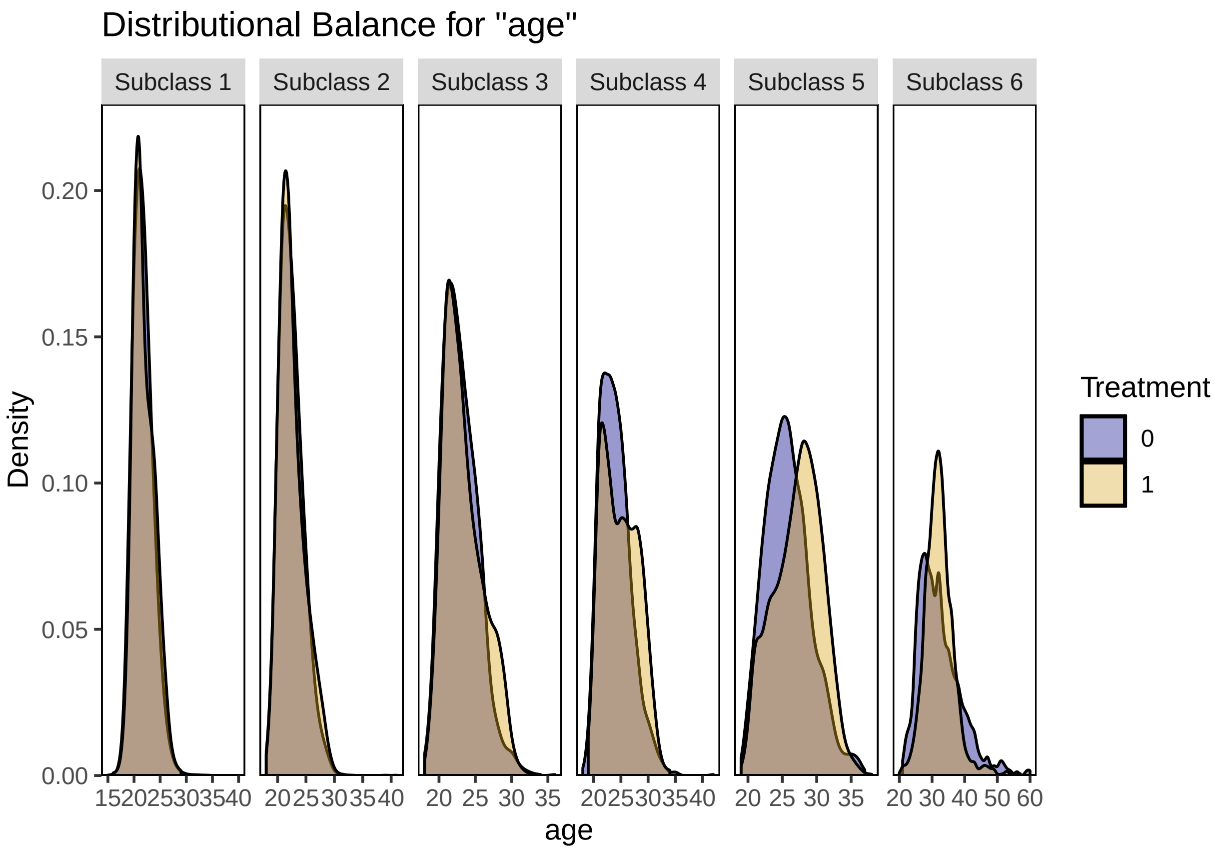
```
plot(ugm.out1, type = "histogram", interactive = TRUE,
     which.xs = ~ cgpa + age + gender + level + reg + coll + prog,
     family = "Times",
     cex.main = 1.5,
     cex.sub = 1,
```

```
     cex.lab = 1,
     cex.axis = 1,
     col.main = "black",
     col.lab = "black",
     col.axis = "black")
```

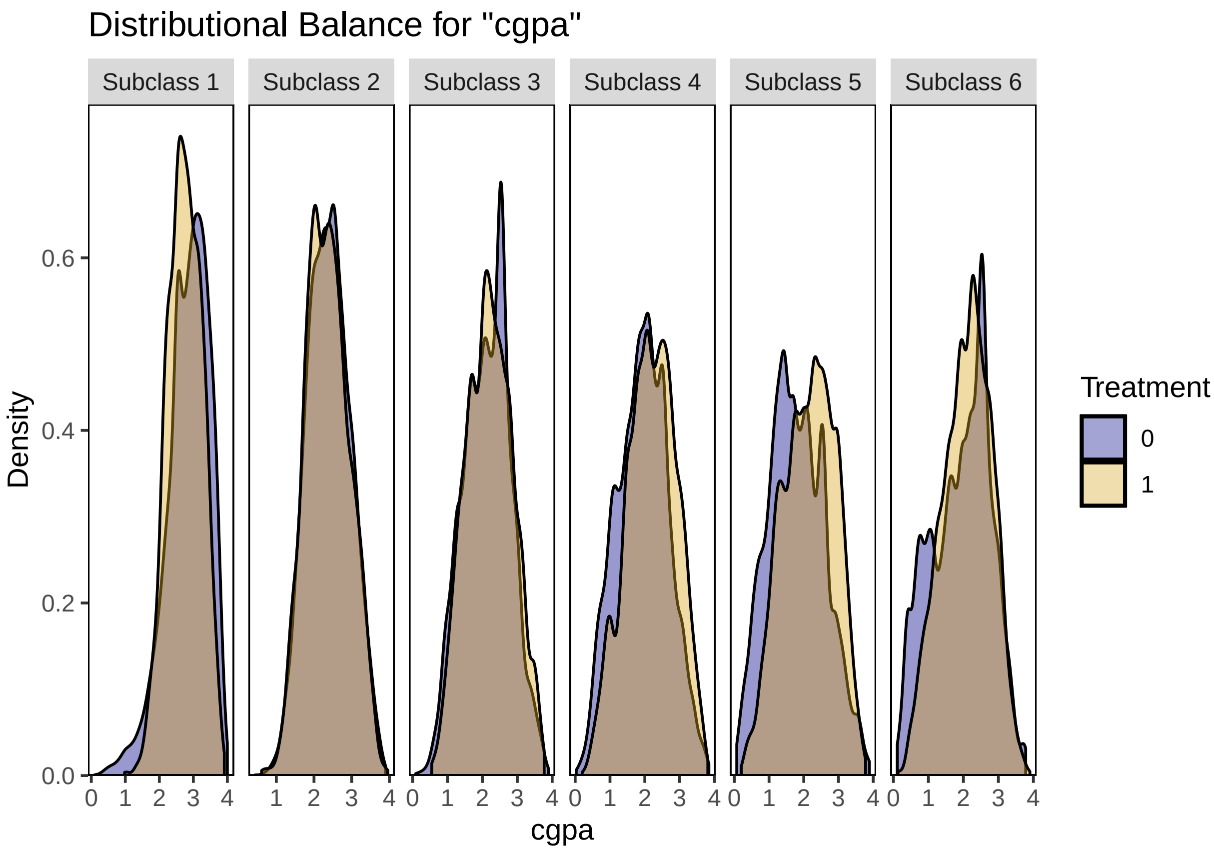


Distributional balance - covariate balance

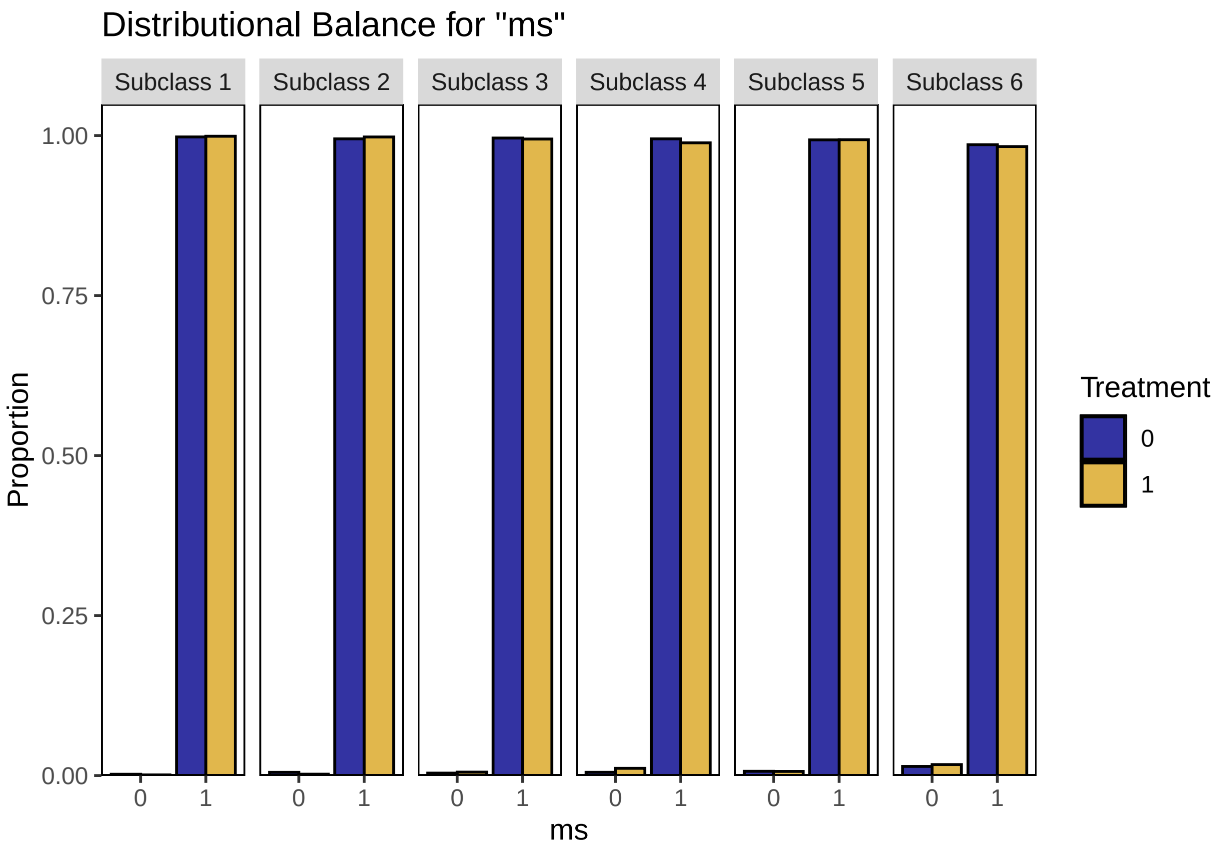
```
bal.plot(ugm.out1, var.name = "age",
         colors = c("darkblue", "goldenrod"))
```



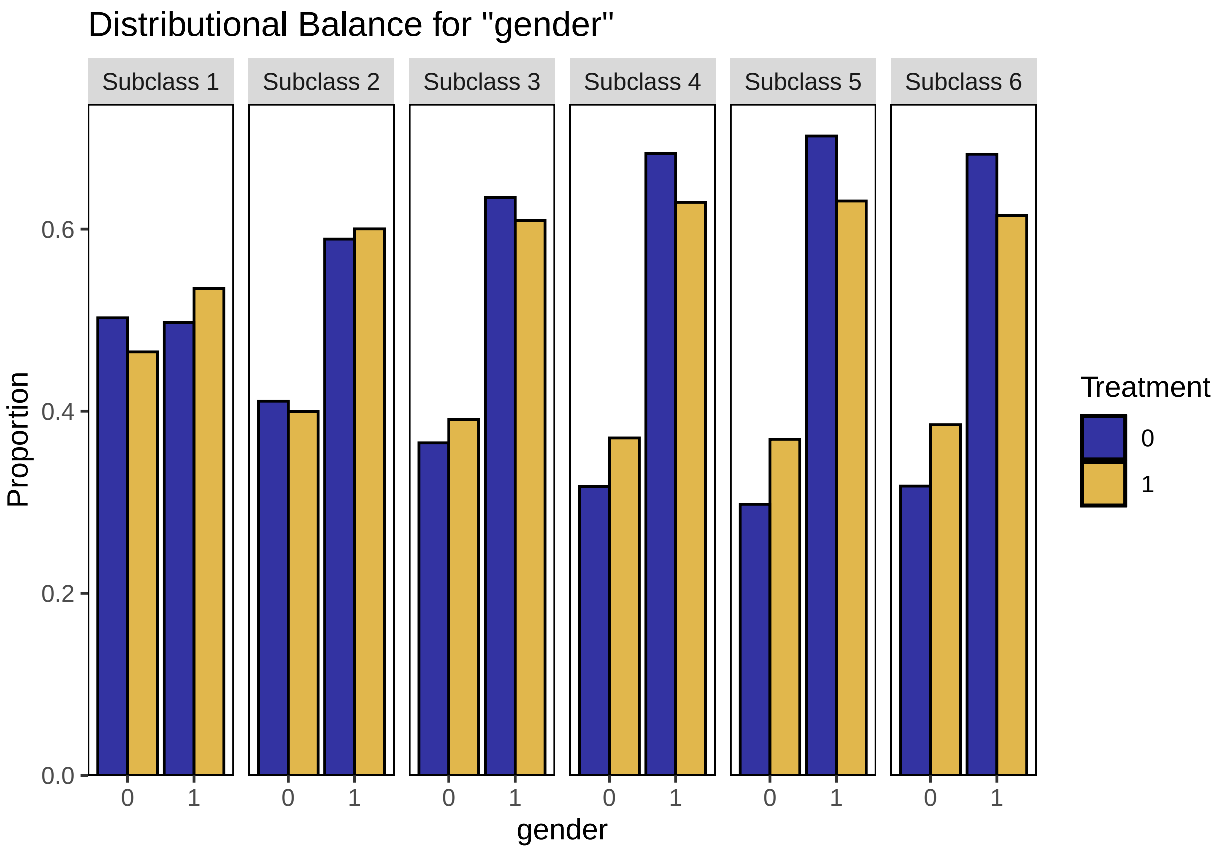

```
bal.plot(ugm.out1, var.name = "cgpa",
         colors = c("darkblue", "goldenrod"))
```



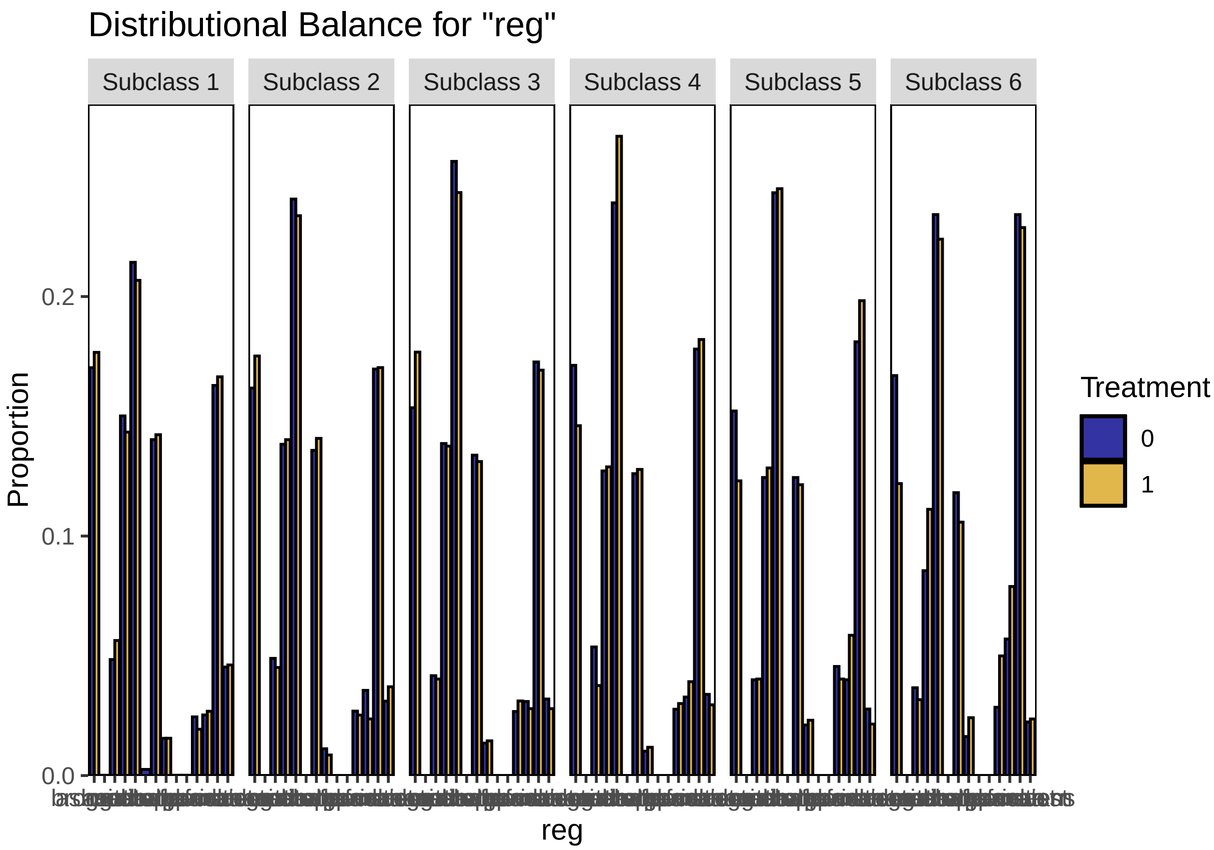

```
bal.plot(ugm.out1, var.name = "ms",
         colors = c("darkblue", "goldenrod"))
```



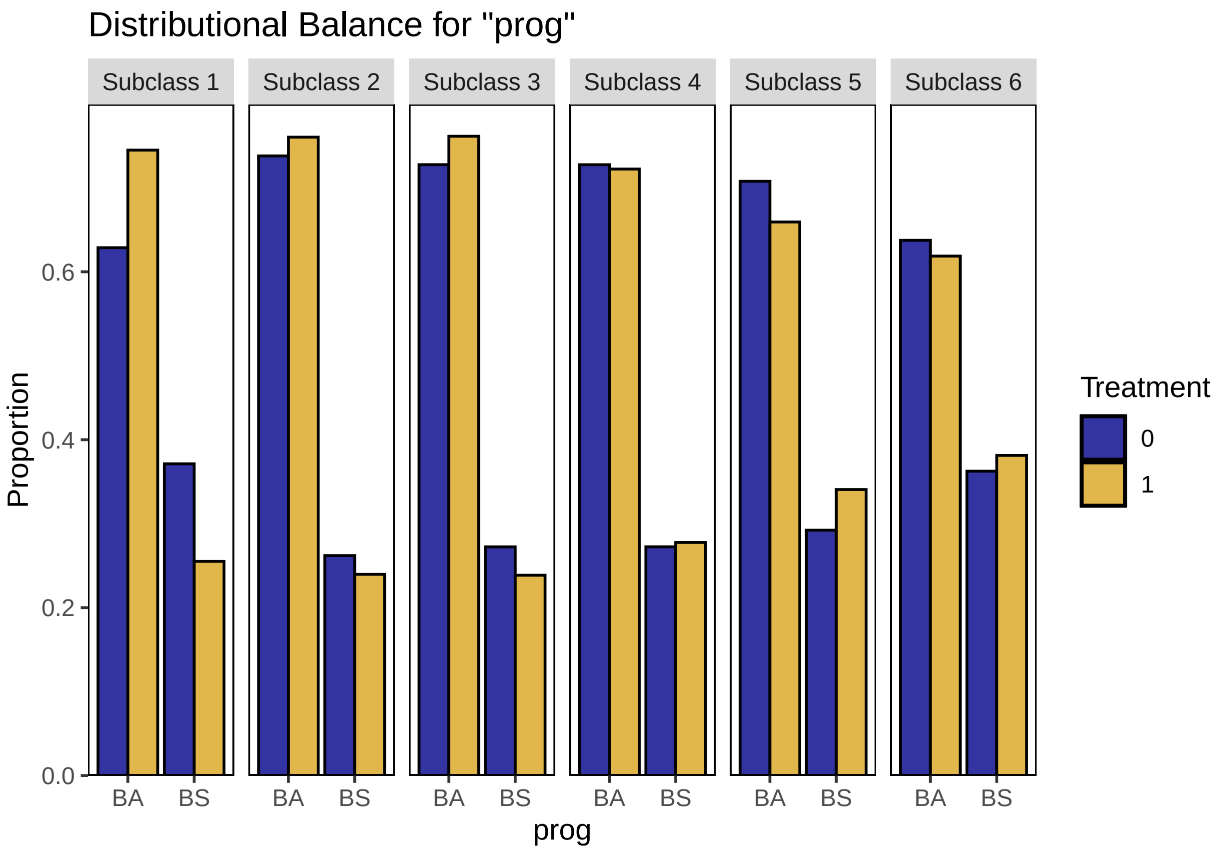

```
bal.plot(ugm.out1, var.name = "gender",
         colors = c("darkblue", "goldenrod"))
```




```
bal.plot(ugm.out1, var.name = "reg",
         colors = c("darkblue", "goldenrod"))
```

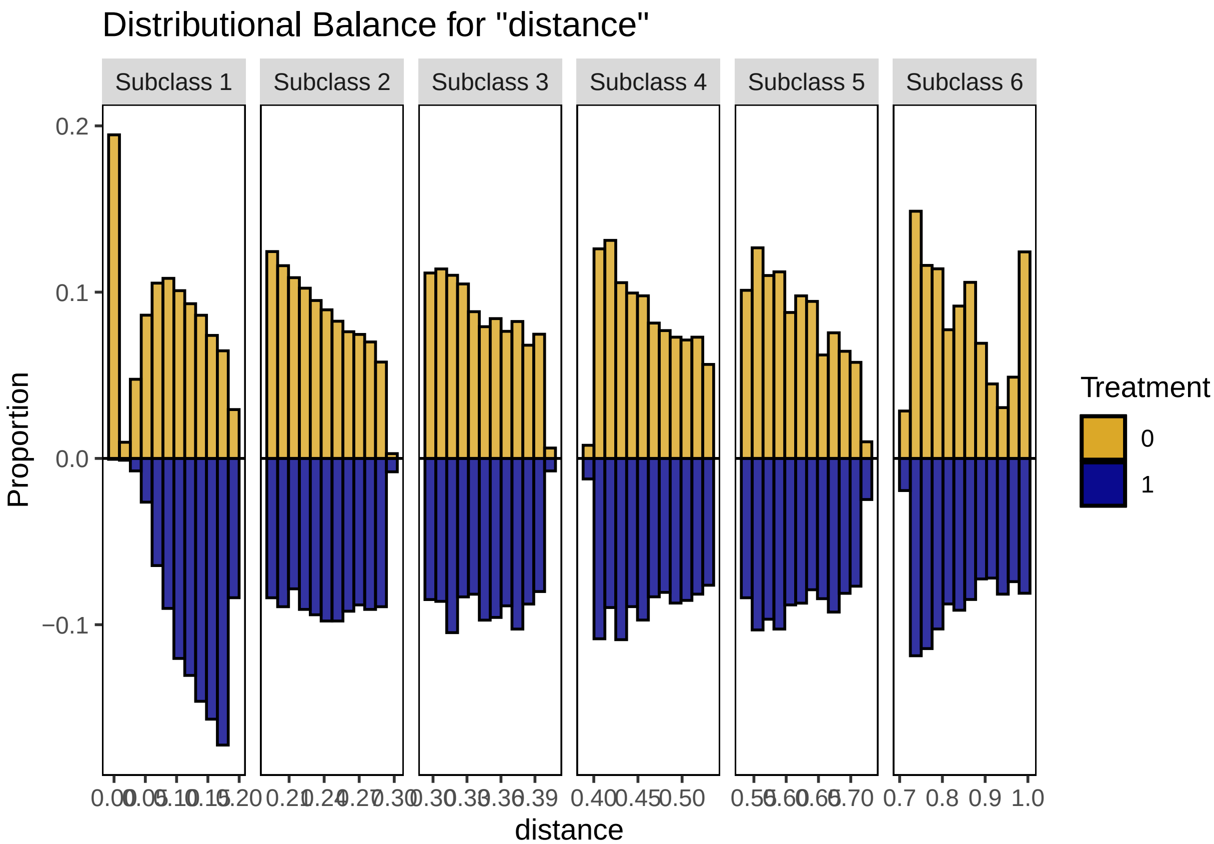



```r
bal.plot(ugm.out1, var.name = "prog",
         colors = c("darkblue", "goldenrod"))
```



Distributional balance of distance

```
bal.plot(ugm.out1, var.name = "distance",
         which = "both",
         type = "histogram",
         colors = c("goldenrod", "darkblue"),
         mirror = TRUE)
```



Distributional Balance for "distance"
Subclass 1
Subclass 2
Subclass 3
Subclass 4
Subclass 5
Subclass 6
Proportion
distance
Treatment
0
1

Estimating effect

```r
#Logistic regression on MatchIt output to estimate effect
library("marginaleffects")
ug_fit <- lm(cgpa ~ treat * (age + gender + ms + level + reg + coll + prog),
             data = ugm.data, weights = weights)
summary(ug_fit)
```

```
##
## Call:
## lm(formula = cgpa ~ treat * (age + gender + ms + level + reg +
##     coll + prog), data = ugm.data, weights = weights)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -7.0876 -0.1222  0.2647  0.5449  5.3874
##
## Coefficients: (4 not defined because of singularities)
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)               2.404e+00  5.883e-02  40.864  < 2e-16 ***
## treat                     4.365e-01  7.270e-01   0.600 0.548216
## age                       1.048e-02  9.548e-04  10.978  < 2e-16 ***
## gender                   -1.296e-01  8.130e-03 -15.940  < 2e-16 ***
## ms                       -4.207e-01  4.940e-02  -8.516  < 2e-16 ***
## level                     6.803e-05  2.854e-05   2.383 0.017155 *
## regasia                   9.395e-02  8.308e-01   0.113 0.909972
## regbrong ahafo           -1.216e-01  2.050e-02  -5.929 3.07e-09 ***
## regcentral                1.544e-01  1.441e-02  10.710  < 2e-16 ***
## regeastern                2.904e-02  1.238e-02   2.345 0.019037 *
## regecowas                -1.579e-01  1.862e-01  -0.848 0.396217
## reggreater accra          1.167e-01  1.433e-02   8.142 3.99e-16 ***
## regnorthern               1.592e-01  3.324e-02   4.790 1.68e-06 ***
## regother african          1.631e-01  8.308e-01   0.196 0.844331
## regother ghanaians       -6.272e-01  8.309e-01  -0.755 0.450348
## regupper east             1.432e-01  2.421e-02   5.916 3.31e-09 ***
## regupper west             1.513e-01  2.227e-02   6.797 1.08e-11 ***
## regvolta                  1.461e-01  1.314e-02  11.123  < 2e-16 ***
## regwestern                1.402e-03  2.351e-02   0.060 0.952429
## colleducation            -3.340e-02  2.392e-02  -1.396 0.162623
## collhealth sciences      -1.514e-02  2.428e-02  -0.624 0.532923
## collhumanities           -2.956e-02  2.306e-02  -1.282 0.199955
## collunknown              -9.008e-01  2.577e-02 -34.956  < 2e-16 ***
## progBS                    5.212e-02  9.001e-03   5.790 7.08e-09 ***
## treat:age                 1.090e-03  1.992e-03   0.547 0.584184
## treat:gender              8.780e-02  1.640e-02   5.354 8.63e-08 ***
## treat:ms                  1.136e-02  9.445e-02   0.120 0.904260
## treat:level              -1.369e-04  5.714e-05  -2.396 0.016595 *
## treat:regasia                    NA         NA      NA       NA
## treat:regbrong ahafo      1.650e-01  4.276e-02   3.859 0.000114 ***
## treat:regcentral         -1.176e-01  2.935e-02  -4.006 6.18e-05 ***
## treat:regeastern         -1.368e-02  2.553e-02  -0.536 0.592027
## treat:regecowas                  NA         NA      NA       NA
## treat:reggreater accra   -7.703e-02  2.949e-02  -2.612 0.009016 **
```

```
## treat:regnorthern          1.320e-02  6.540e-02   0.202 0.840055
## treat:regother african            NA         NA      NA       NA
## treat:regother ghanaians          NA         NA      NA       NA
## treat:regupper east       -8.801e-02  4.814e-02  -1.828 0.067497 .
## treat:regupper west       -8.682e-02  4.373e-02  -1.985 0.047124 *
## treat:regvolta            -8.215e-02  2.694e-02  -3.049 0.002298 **
## treat:regwestern           6.054e-02  4.846e-02   1.249 0.211553
## treat:colleducation       -4.534e-01  7.195e-01  -0.630 0.528580
## treat:collhealth sciences -1.910e-01  7.195e-01  -0.266 0.790605
## treat:collhumanities      -4.301e-01  7.193e-01  -0.598 0.549907
## treat:collunknown         -1.067e-01  7.198e-01  -0.148 0.882116
## treat:progBS               4.651e-02  1.826e-02   2.548 0.010837 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7185 on 46045 degrees of freedom
## Multiple R-squared:  0.1305, Adjusted R-squared:  0.1297
## F-statistic: 168.6 on 41 and 46045 DF,  p-value: < 2.2e-16
```

```
ugm_comp <- comparisons(ug_fit,
                     variables = "treat",
                     vcov = ~subclass,
                     newdata = subset(ugm.data, treat == 1),
                     wts = "weights")
summary(ugm_comp)
```

```
##
##   Term          Contrast Estimate Std. Error z Pr(>|z|)   2.5 % 97.5 %
##  treat mean(1) - mean(0)   0.0922      0.046 2    0.045 0.00206  0.182
##
## Columns: term, contrast, estimate, std.error, statistic, p.value, conf.low, conf.high
```

Checking balance

Assessing balance numerically

```
balance.table <- bal.tab(ugm.out1, stats = c("c", "m"), un=TRUE,
                         weights = "distance", binary = "std",
                         continuous = "std",
        thresholds = c(cor = .1), poly = 3)
```

```
## Warning: The following variable(s) named in 'weights' are not in any available
## data sets and will be ignored: distance.
```

```
print(balance.table)
```

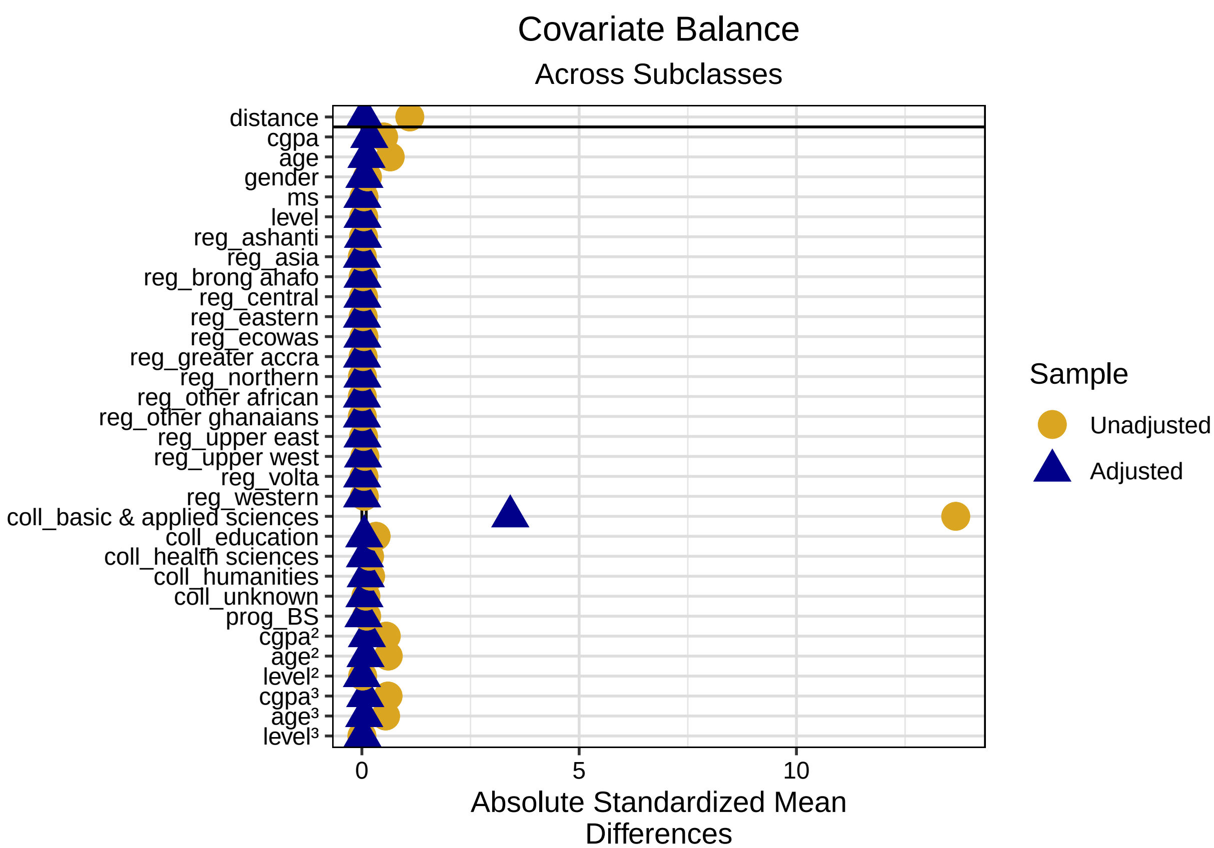
```
## Balance measures across subclasses
##                                    Type  Diff.Un Diff.Adj
## distance                       Distance   1.1028   0.0567
## cgpa                            Contin.  -0.5004   0.1705
## age                             Contin.   0.6519   0.1061
## gender                           Binary   0.1281  -0.0576
## ms                               Binary  -0.0487  -0.0129
## level                           Contin.   0.0428   0.0159
## reg_ashanti                      Binary  -0.0384  -0.0261
## reg_asia                         Binary  -0.0106  -0.0027
## reg_brong ahafo                  Binary  -0.0297  -0.0150
## reg_central                      Binary  -0.0384   0.0125
## reg_eastern                      Binary   0.0292  -0.0032
## reg_ecowas                       Binary  -0.0477  -0.0119
## reg_greater accra                Binary  -0.0280  -0.0046
## reg_northern                     Binary   0.0136   0.0130
## reg_other african                Binary  -0.0106  -0.0027
## reg_other ghanaians              Binary  -0.0106  -0.0027
## reg_upper east                   Binary   0.0385   0.0151
## reg_upper west                   Binary   0.0690   0.0277
## reg_volta                        Binary   0.0485   0.0071
## reg_western                      Binary  -0.0556  -0.0063
## coll_basic & applied sciences    Binary -13.6654  -3.4150
## coll_education                   Binary   0.3276  -0.0542
## coll_health sciences             Binary   0.1767   0.0705
## coll_humanities                  Binary  -0.2006   0.0891
## coll_unknown                     Binary   0.0924  -0.0591
## prog_BS                          Binary  -0.1099  -0.0368
## cgpa²                           Contin.  -0.5613   0.1168
## age²                            Contin.   0.6070   0.0842
## level²                          Contin.   0.0169  -0.0016
## cgpa³                           Contin.  -0.6027   0.0776
## age³                            Contin.   0.5460   0.0532
## level³                          Contin.   0.0008  -0.0145
##
## Sample sizes by subclass
##             1    2    3    4    5    6   All
## Control 23342 5538 2878 1769  900  491 34918
```

```
## Treated  1862 1861 1861 1862 1861 1862 11169
## Total   25204 7399 4739 3631 2761 2353 46087
```

Assessing balance - covariate balance (Absolute Mean Differences)

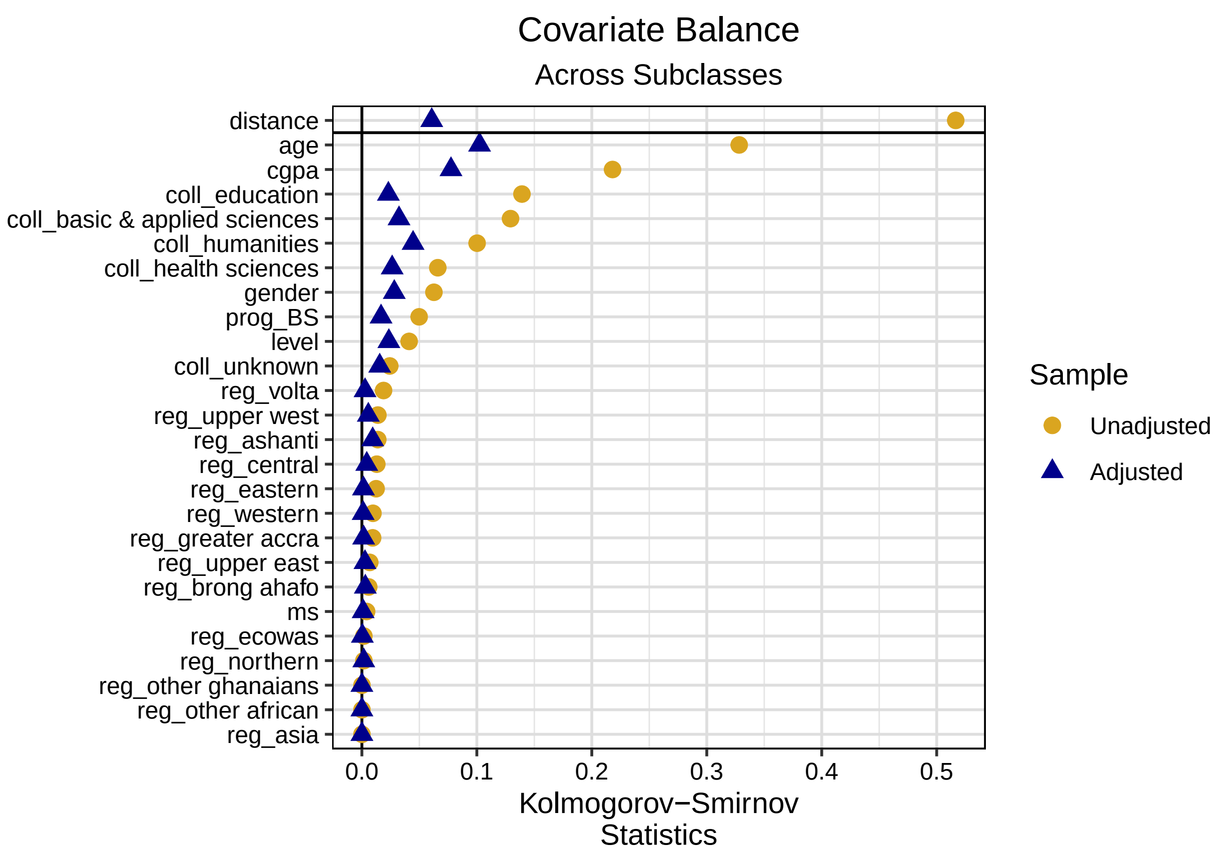
```
love.plot(balance.table,
          threshold =.1,
          line = FALSE,
          grid = TRUE,
          stars = "std",
          labels = TRUE,
          abs= TRUE,
          colors = c("goldenrod", "darkblue"),
          shapes = c("circle", "triangle"),
          size = 5,
          cex.main = 1.5,
          cex.sub = 1,
          cex.lab = 1,
          cex.axis = 1)
```

```
## Warning: Large mean differences detected; you may not be using standardized
## mean differences for continuous variables.
```



Assessing balance - Kolmogorov-Smirnov Statistics

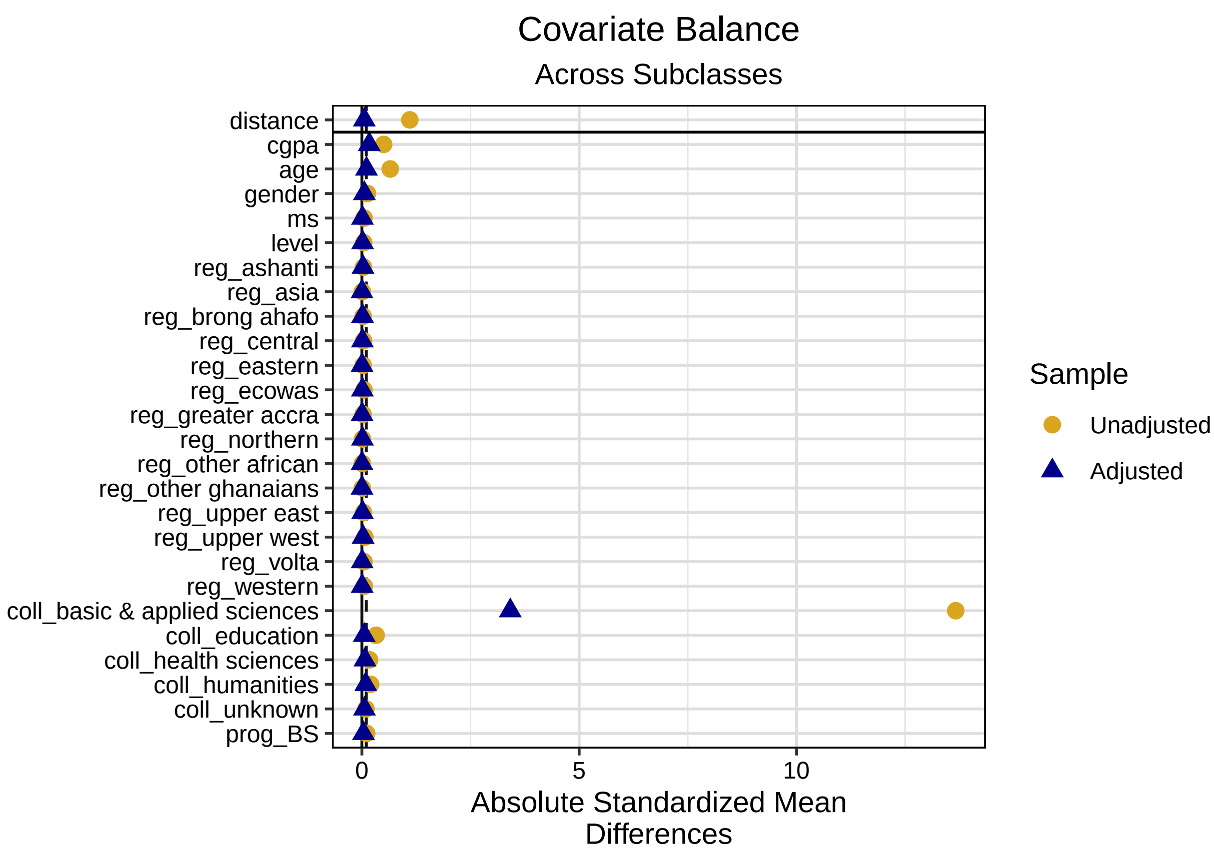
```
love.plot(ugm.out1, stats = c("c", "ks"),
          thresholds = c(cor = .1),
          abs = TRUE, wrap = 20,
          var.order = "unadjusted",
          line = FALSE,
          grid = TRUE,
          labels = TRUE,
          colors = c("goldenrod", "darkblue"),
          shapes = c("circle", "triangle"),
          size = 3,
          cex.main = 1.5,
          cex.sub = 1,
          cex.lab = 1,
          cex.axis = 1)
```



Assessing balance - covariate blanace (Standardized Mean Difference)

```
love.plot(ugm.out1, binary = "std", thresholds = c(m = .1),
          labels = TRUE,
          line = FALSE,
          grid = TRUE,
          abs= TRUE, colors = c("goldenrod", "darkblue"),
          shapes = c("circle", "triangle"),
          size = 3,
          cex.main = 1.5,
          cex.sub = 1,
          cex.lab = 1,
          cex.axis = 1)
```

```
## Warning: Large mean differences detected; you may not be using standardized
## mean differences for continuous variables.
```

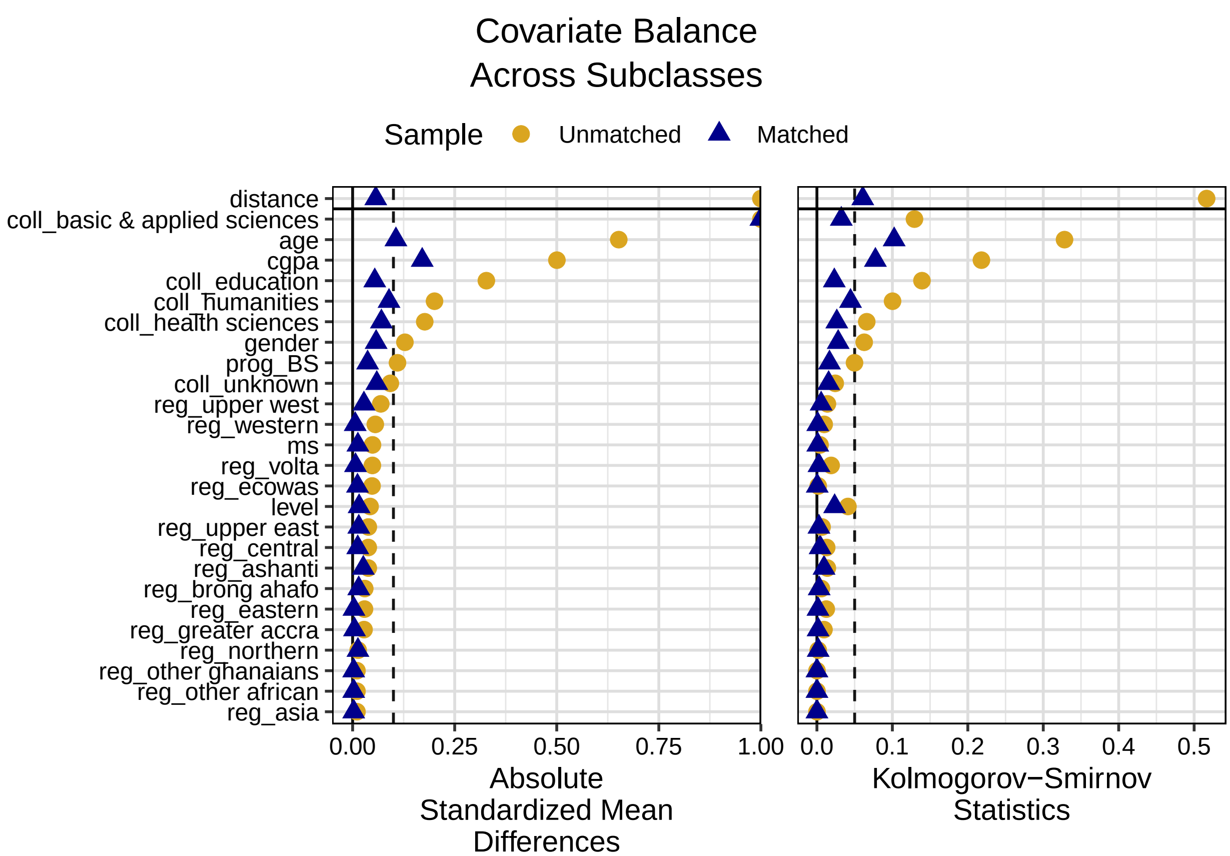


Assessing balance- covariate balance

(Standardized Mean Difference and Kolmogorov-Smirnov Statistics)

```r
love.plot(ugm.out1, stats = c("mean.diffs", "ks.statistics"),
          threshold = c(m = .1, ks = .05),
          binary = "std",
          abs = TRUE,
          var.order = "unadjusted",
          var.names = NULL,
          limits = c(0, 1),
          grid = TRUE,
          wrap = 20,
          sample.names = c("Unmatched", "Matched"),
          position = "top",
          shapes = c("circle", "triangle"),
          colors = c("goldenrod", "darkblue"),
          size = 3)
```

```
## Warning: Large mean differences detected; you may not be using standardized
## mean differences for continuous variables.
```



Addis Ababa University

Descriptive Statistics

Summary

AAU Dataset

```
dfSummary(aau_desc_all,
          plain.ascii  = TRUE,
          style        = "grid",
          graph.magnif = 0.85,
          valid.col    = TRUE)
```

Data Frame Summary
aau_desc_all
Dimensions: 4051 x 11
Duplicates: 0

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
1	uid [character]	1. 00/7739//11 2. 000012/10 3. 000013/10 4. 000016/11 5. 000021/10 6. 000021/11 7. 000022/11 8. 000023/10 9. 000025/11 10. 000026/10 [4041 others]	1 (0.0%) 1 (0.0%) 1 (0.0%) 1 (0.0%) 1 (0.0%) 1 (0.0%) 1 (0.0%) 1 (0.0%) 1 (0.0%) 1 (0.0%) 4041 (99.8%)	IIIIIIIIIIIIIIIIIII	4051 (100.0%)	0 (0.0%)
2	age [numeric]	Mean (sd) : 35.4 (8.8) min < med < max: -1 < 35 < 70 IQR (CV) : 9 (0.2)	58 distinct values	: : : : : : : : : . : : : : .	4051 (100.0%)	0 (0.0%)
3	gender [numeric]	Min : 0 Mean : 0.7 Max : 1	0 : 1088 (26.9%) 1 : 2963 (73.1%)	IIIII IIIIIIIIIIIIII	4051 (100.0%)	0 (0.0%)

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
4	cgpa [numeric]	Mean (sd) : 3.5 (0.4) min < med < max: 0.9 < 3.5 < 4 IQR (CV) : 0.5 (0.1)	201 distinct values	: : : : : : : : : : : :	4051 (100.0%)	0 (0.0%)
5	modality [numeric]	Min : 0 Mean : 0.3 Max : 1	0 : 3036 (74.9%) 1 : 1015 (25.1%)	IIIIIIIIIIIIII IIIII	4051 (100.0%)	0 (0.0%)
6	region [character]	1. addis ababa 2. amhara 3. gambela 4. not set 5. oromia 6. other 7. snnpr 8. tigray	266 (6.6%) 5 (0.1%) 1 (0.0%) 1952 (48.2%) 7 (0.2%) 1812 (44.7%) 4 (0.1%) 4 (0.1%)	I IIIIIIIII IIIIIIII	4051 (100.0%)	0 (0.0%)
7	year [numeric]	Mean (sd) : 1.6 (0.8) min < med < max: 1 < 1 < 6 IQR (CV) : 1 (0.5)	1 : 2240 (55.3%) 2 : 1366 (33.7%) 3 : 345 (8.5%) 4 : 91 (2.2%) 5 : 4 (0.1%) 6 : 5 (0.1%)	IIIIIIIIIII IIIIII I	4051 (100.0%)	0 (0.0%)
8	term [character]	1. first 2. second	3489 (86.1%) 562 (13.9%)	IIIIIIIIIIIIIIIII II	4051 (100.0%)	0 (0.0%)
9	prog [character]	1. LLM 2. MA 3. MBA 4. MSC 5. MSW 6. PhD	184 (4.5%) 1880 (46.4%) 201 (5.0%) 909 (22.4%) 64 (1.6%) 813 (20.1%)	IIIIIIIII IIII IIII	4051 (100.0%)	0 (0.0%)
10	dept [character]	1. school of commerce 2. MBA 3. school of law 4. department of accounting 5. school of journalism & co 6. center for environment an 7. school of earth sciences 8. foreign languages and lit 9. biotechnology 10. center for food science & [48 others]	1011 (25.0%) 201 (5.0%) 200 (4.9%) 163 (4.0%) 148 (3.7%) 145 (3.6%) 116 (2.9%) 103 (2.5%) 99 (2.4%) 94 (2.3%) 1771 (43.7%)	IIII IIIIIIII	4051 (100.0%)	0 (0.0%)

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
11	coll [character]	1. school of commerce 2. sciences 3. business & econ 4. social sciences 5. humanities 6. development studies 7. law 8. edu 9. biotech 10. arts [2 others]	1011 (25.0%) 821 (20.3%) 465 (11.5%) 374 (9.2%) 359 (8.9%) 318 (7.8%) 269 (6.6%) 180 (4.4%) 99 (2.4%) 57 (1.4%) 98 (2.4%)	IIII IIII II I I I I	4051 (100.0%)	0 (0.0%)

AAU Campus

```r
dfSummary(aau_desc_campus,
          plain.ascii  = TRUE,
          style        = "grid",
          graph.magnif = 0.85,
          valid.col    = TRUE)
```

Data Frame Summary
aau_desc_campus
Dimensions: 3036 x 12
Duplicates: 0

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
1	uid [character]	1. 00/7739//11 2. 000012/10 3. 000013/10 4. 000016/11 5. 000021/10 6. 000021/11 7. 000022/11 8. 000023/10 9. 000025/11 10. 000026/10 [3026 others]	1 (0.0%) 1 (0.0%) 1 (0.0%) 1 (0.0%) 1 (0.0%) 1 (0.0%) 1 (0.0%) 1 (0.0%) 1 (0.0%) 1 (0.0%) 3026 (99.7%)	IIIIIIIIIIIIIIIIIII	3036 (100.0%)	0 (0.0%)
2	age [numeric]	Mean (sd) : 34.8 (8) min < med < max: -1 < 34 < 70 IQR (CV) : 9 (0.2)	55 distinct values	: : : : : : . : : : : .	3036 (100.0%)	0 (0.0%)
3	gender [numeric]	Min : 0 Mean : 0.7 Max : 1	0 : 796 (26.2%) 1 : 2240 (73.8%)	IIIII IIIIIIIIIIIIII	3036 (100.0%)	0 (0.0%)
4	cgpa [numeric]	Mean (sd) : 3.2 (1.1) min < med < max: 0 < 3.5 < 4 IQR (CV) : 0.6 (0.3)	162 distinct values	: : : : : : : . : :	3036 (100.0%)	0 (0.0%)
5	modality [numeric]	1 distinct value	0 : 3036 (100.0%)	IIIIIIIIIIIIIIIIIII	3036 (100.0%)	0 (0.0%)
6	region [character]	1. addis ababa 2. amhara 3. gambela 4. not set 5. oromia 6. other 7. snnpr 8. tigray	193 (6.4%) 5 (0.2%) 1 (0.0%) 1090 (35.9%) 7 (0.2%) 1732 (57.0%) 4 (0.1%) 4 (0.1%)	I IIIIIII IIIIIIIIIII	3036 (100.0%)	0 (0.0%)

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
7	year [numeric]	Mean (sd) : 1.6 (0.8) min < med < max: 1 < 1 < 6 IQR (CV) : 1 (0.5)	1 : 1591 (52.4%) 2 : 1203 (39.6%) 3 : 142 (4.7%) 4 : 91 (3.0%) 5 : 4 (0.1%) 6 : 5 (0.2%)	IIIIIIIIII IIIIIII	3036 (100.0%)	0 (0.0%)
8	term [character]	1. first 2. second	2925 (96.3%) 111 (3.7%)	IIIIIIIIIIIIIIIIIII	3036 (100.0%)	0 (0.0%)
9	prog [character]	1. LLM 2. MA 3. MBA 4. MSC 5. MSW 6. PhD	184 (6.1%) 1063 (35.0%) 141 (4.6%) 800 (26.4%) 35 (1.2%) 813 (26.8%)	I IIIIIII IIIII IIIII	3036 (100.0%)	0 (0.0%)
10	dept [character]	1. school of commerce 2. school of law 3. school of journalism & co 4. center for environment an 5. school of earth sciences 6. master of business admini 7. foreign languages and lit 8. biotechnology 9. center for food science & 10. department of cellular, m [48 others]	208 (6.9%) 200 (6.6%) 148 (4.9%) 145 (4.8%) 116 (3.8%) 112 (3.7%) 103 (3.4%) 99 (3.3%) 94 (3.1%) 92 (3.0%) 1719 (56.6%)	I I IIIIIIIIIII	3036 (100.0%)	0 (0.0%)
11	coll [character]	1. sciences 2. humanities 3. social sciences 4. development studies 5. business & econ 6. law 7. school of commerce 8. edu 9. biotech 10. arts [2 others]	821 (27.0%) 359 (11.8%) 341 (11.2%) 318 (10.5%) 286 (9.4%) 269 (8.9%) 208 (6.9%) 180 (5.9%) 99 (3.3%) 57 (1.9%) 98 (3.2%)	IIIII II II II I I I I	3036 (100.0%)	0 (0.0%)

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
12	dob [character]	1. NA 2. 43879 3. 32669 4. 33675 5. 29567 6. 30937 7. 31692 8. 31741 9. 32268 10. 32875 [2319 others]	183 (6.0%) 10 (0.3%) 5 (0.2%) 5 (0.2%) 4 (0.1%) 4 (0.1%) 4 (0.1%) 4 (0.1%) 4 (0.1%) 4 (0.1%) 2809 (92.5%)	I IIIIIIIIIIIIIIIII	3036 (100.0%)	0 (0.0%)

AAU Online

```
dfSummary(aau_desc_online,
          plain.ascii  = TRUE,
          style        = "grid",
          graph.magnif = 0.85,
          valid.col    = TRUE)
```

Data Frame Summary
aau_desc_online
Dimensions: 1015 x 12
Duplicates: 0

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
1	uid [character]	1. gsd/0004/11 2. gsd/0009/11 3. gsd/0012/10 4. gsd/0017/11 5. gsd/0020/11 6. gsd/0024/07 7. gsd/0030/09 8. gsd/0037/11 9. gsd/0052/08 10. gsd/0053/11 [1005 others]	1 (0.1%) 1 (0.1%) 1 (0.1%) 1 (0.1%) 1 (0.1%) 1 (0.1%) 1 (0.1%) 1 (0.1%) 1 (0.1%) 1 (0.1%) 1005 (99.0%)	IIIIIIIIIIIIIIIIIII	1015 (100.0%)	0 (0.0%)
2	age [numeric]	Mean (sd) : 37 (10.5) min < med < max: 3 < 38 < 68 IQR (CV) : 10 (0.3)	45 distinct values	: : : : : : : . . : : : :	1015 (100.0%)	0 (0.0%)
3	gender [numeric]	Min : 0 Mean : 0.7 Max : 1	0 : 292 (28.8%) 1 : 723 (71.2%)	IIIII IIIIIIIIIIIIII	1015 (100.0%)	0 (0.0%)
4	cgpa [numeric]	Mean (sd) : 2.7 (1.3) min < med < max: 0 < 3.2 < 4 IQR (CV) : 0.6 (0.5)	173 distinct values	: : : . : . : : . : : :	1015 (100.0%)	0 (0.0%)
5	modality [numeric]	1 distinct value	1 : 1015 (100.0%)	IIIIIIIIIIIIIIIIIIII	1015 (100.0%)	0 (0.0%)
6	region [character]	1. addis ababa 2. not set 3. other	73 (7.2%) 862 (84.9%) 80 (7.9%)	I IIIIIIIIIIIIIIII I	1015 (100.0%)	0 (0.0%)
7	year [numeric]	Mean (sd) : 1.6 (0.8) min < med < max: 1 < 1 < 3 IQR (CV) : 1 (0.5)	1 : 649 (63.9%) 2 : 163 (16.1%) 3 : 203 (20.0%)	IIIIIIIIIIII III IIII	1015 (100.0%)	0 (0.0%)

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
8	term [character]	1. first 2. second	564 (55.6%) 451 (44.4%)	IIIIIIIIIII IIIIIIII	1015 (100.0%)	0 (0.0%)
9	prog [character]	1. MA 2. MBA 3. MSC 4. MSW	700 (69.0%) 192 (18.9%) 90 (8.9%) 33 (3.3%)	IIIIIIIIIIIII III I	1015 (100.0%)	0 (0.0%)
10	dept [character]	1. department of accounting 2. master of business admini 3. school of commerce 4. school of social work	90 (8.9%) 89 (8.8%) 803 (79.1%) 33 (3.3%)	I I IIIIIIIIIIIIIII	1015 (100.0%)	0 (0.0%)
11	coll [character]	1. business & econ 2. school of commerce 3. social sciences	179 (17.6%) 803 (79.1%) 33 (3.3%)	III IIIIIIIIIIIIIII	1015 (100.0%)	0 (0.0%)
12	dob [character]	1. NA 2. 43012 3. 42578 4. 43617 5. 30792 6. 31487 7. 44427 8. 24067 9. 25643 10. 26387 [847 others]	66 (6.5%) 23 (2.3%) 17 (1.7%) 4 (0.4%) 3 (0.3%) 3 (0.3%) 3 (0.3%) 2 (0.2%) 2 (0.2%) 2 (0.2%) 890 (87.7%)	I IIIIIIIIIIIIIIIII	1015 (100.0%)	0 (0.0%)

Common descriptive statistics

AAU Dataset

```
descr(aau_desc_all)
```

```
## Non-numerical variable(s) ignored: uid, region, term, prog, dept, coll
```

Descriptive Statistics

aau_desc_all
N: 4051

	age	cgpa	gender	modality	year
Mean	35.36	3.46	0.73	0.25	1.59
Std.Dev	8.76	0.37	0.44	0.43	0.76
Min	-1.00	0.88	0.00	0.00	1.00
Q1	31.00	3.27	0.00	0.00	1.00
Median	35.00	3.46	1.00	0.00	1.00
Q3	40.00	3.74	1.00	1.00	2.00
Max	70.00	4.00	1.00	1.00	6.00
MAD	7.41	0.36	0.00	0.00	0.00
IQR	9.00	0.47	1.00	1.00	1.00
CV	0.25	0.11	0.61	1.73	0.48
Skewness	-0.86	-1.65	-1.04	1.15	1.38
SE.Skewness	0.04	0.04	0.04	0.04	0.04
Kurtosis	3.61	6.15	-0.91	-0.68	2.22
N.Valid	4051.00	4051.00	4051.00	4051.00	4051.00
Pct.Valid	100.00	100.00	100.00	100.00	100.00

AAU Campus

```
descr(aau_desc_campus)
```

```
## Non-numerical variable(s) ignored: uid, region, term, prog, dept, coll, dob
```

Descriptive Statistics

aau_desc_campus
N: 3036

	age	cgpa	gender	modality	year
Mean	34.80	3.19	0.74	0.00	1.59
Std.Dev	7.98	1.11	0.44	0.00	0.75
Min	-1.00	0.00	0.00	0.00	1.00
Q1	30.00	3.21	0.00	0.00	1.00
Median	34.00	3.54	1.00	0.00	1.00
Q3	39.00	3.79	1.00	0.00	2.00
Max	70.00	4.00	1.00	0.00	6.00
MAD	5.93	0.42	0.00	0.00	0.00
IQR	9.00	0.58	1.00	0.00	1.00
CV	0.23	0.35	0.60	NaN	0.47
Skewness	-0.48	-2.29	-1.08	NaN	1.56
SE.Skewness	0.04	0.04	0.04	0.04	0.04
Kurtosis	3.73	3.89	-0.83	NaN	3.49
N.Valid	3036.00	3036.00	3036.00	3036.00	3036.00
Pct.Valid	100.00	100.00	100.00	100.00	100.00

AAU Online

```
descr(aau_desc_online)
```

```
## Non-numerical variable(s) ignored: uid, region, term, prog, dept, coll, dob
```

Descriptive Statistics

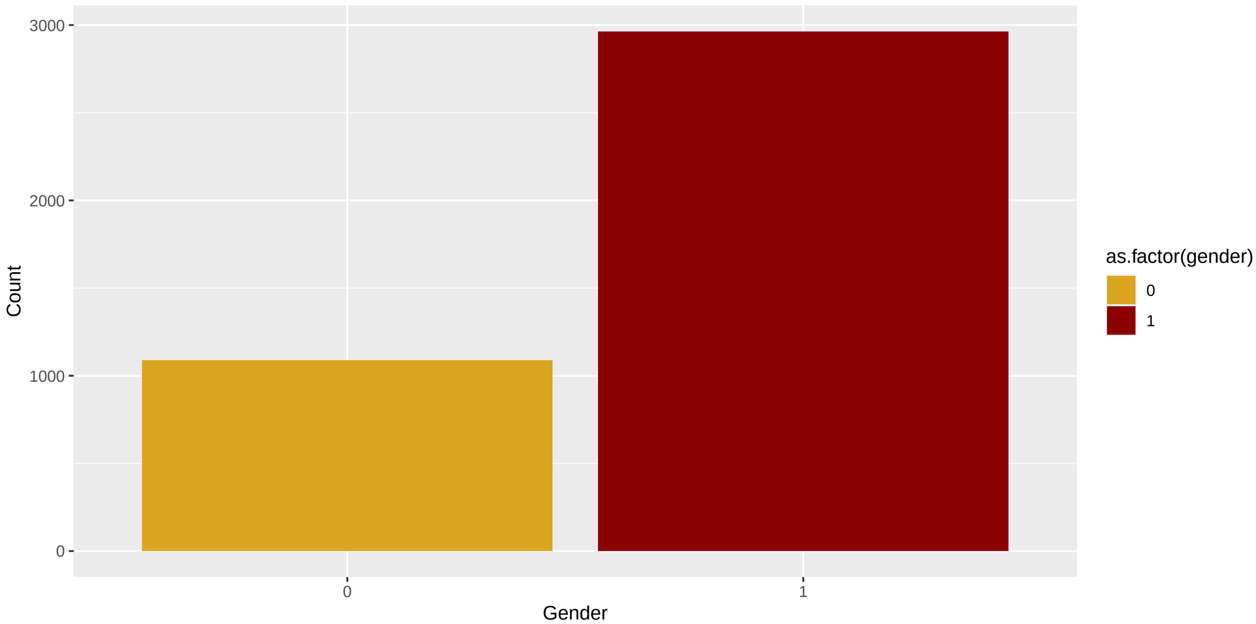
aau_desc_online
N: 1015

	age	cgpa	gender	modality	year
Mean	36.96	2.69	0.71	1.00	1.56
Std.Dev	10.46	1.25	0.45	0.00	0.80
Min	3.00	0.00	0.00	1.00	1.00
Q1	33.00	2.79	0.00	1.00	1.00
Median	38.00	3.18	1.00	1.00	1.00
Q3	43.00	3.44	1.00	1.00	2.00
Max	68.00	4.00	1.00	1.00	3.00
MAD	7.41	0.46	0.00	0.00	0.00
IQR	10.00	0.65	1.00	0.00	1.00
CV	0.28	0.47	0.64	0.00	0.52
Skewness	-1.41	-1.48	-0.94	NaN	0.96
SE.Skewness	0.08	0.08	0.08	0.08	0.08
Kurtosis	3.19	0.60	-1.12	NaN	-0.78
N.Valid	1015.00	1015.00	1015.00	1015.00	1015.00
Pct.Valid	100.00	100.00	100.00	100.00	100.00

Gender

AAU Dataset - Frequency

```
ggplot(aau_desc_all, aes(x=as.factor(gender), fill = as.factor(gender))) +
  geom_bar()+ xlab("Gender") + ylab("Count") +
  scale_fill_manual(values = c("goldenrod", "darkred"))
```



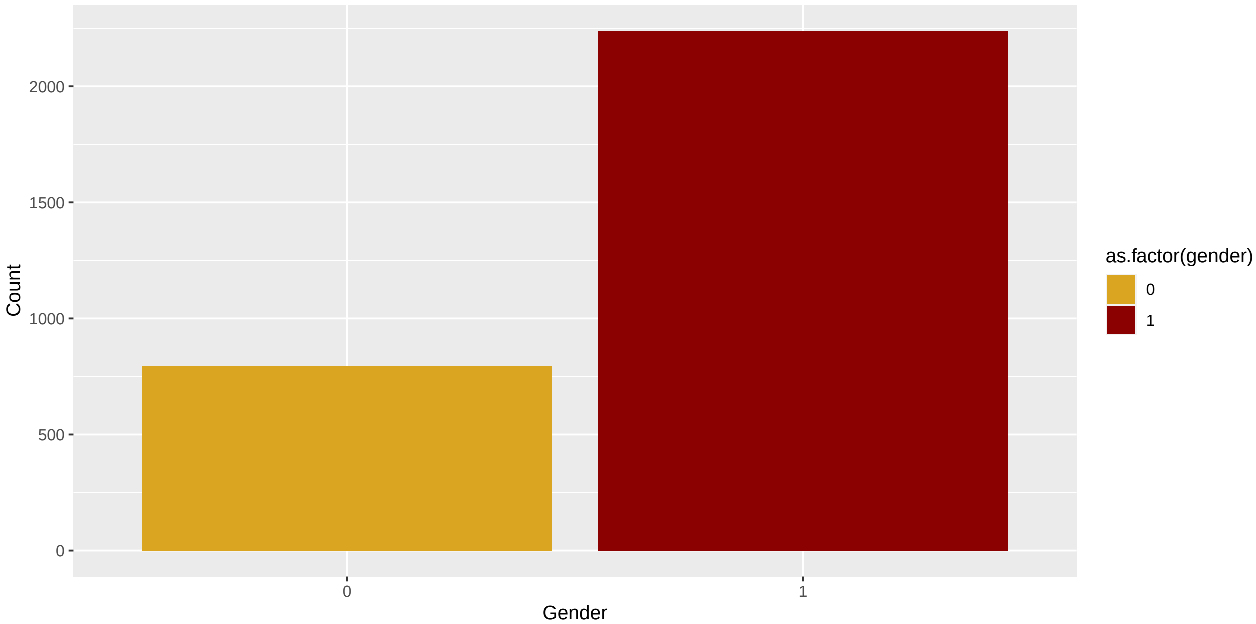
AAU Campus- Frequency

```
freq(aau_desc_campus$gender, plain.ascii = TRUE, style = 'grid')
```

Frequencies
aau_desc_campus$gender
Type: Numeric

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
0	796	26.22	26.22	26.22	26.22
1	2240	73.78	100.00	73.78	100.00
<NA>	0			0.00	100.00
Total	3036	100.00	100.00	100.00	100.00

```r
ggplot(aau_desc_campus, aes(x=as.factor(gender), fill = as.factor(gender))) +
  geom_bar() + xlab("Gender") + ylab("Count") +
  scale_fill_manual(values = c("goldenrod", "darkred"))
```



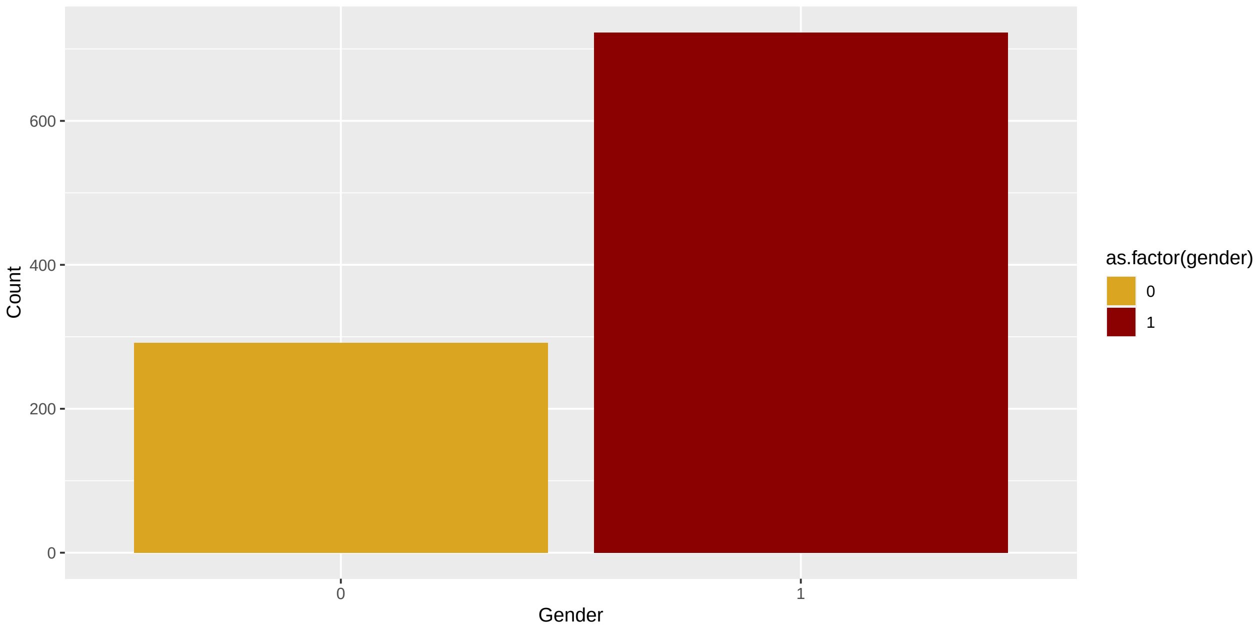
AAU Online- Frequency

```r
freq(aau_desc_online$gender, plain.ascii = TRUE, style = 'grid')
```

Frequencies
aau_desc_online$gender
Type: Numeric

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
0	292	28.77	28.77	28.77	28.77
1	723	71.23	100.00	71.23	100.00
<NA>	0			0.00	100.00
Total	1015	100.00	100.00	100.00	100.00

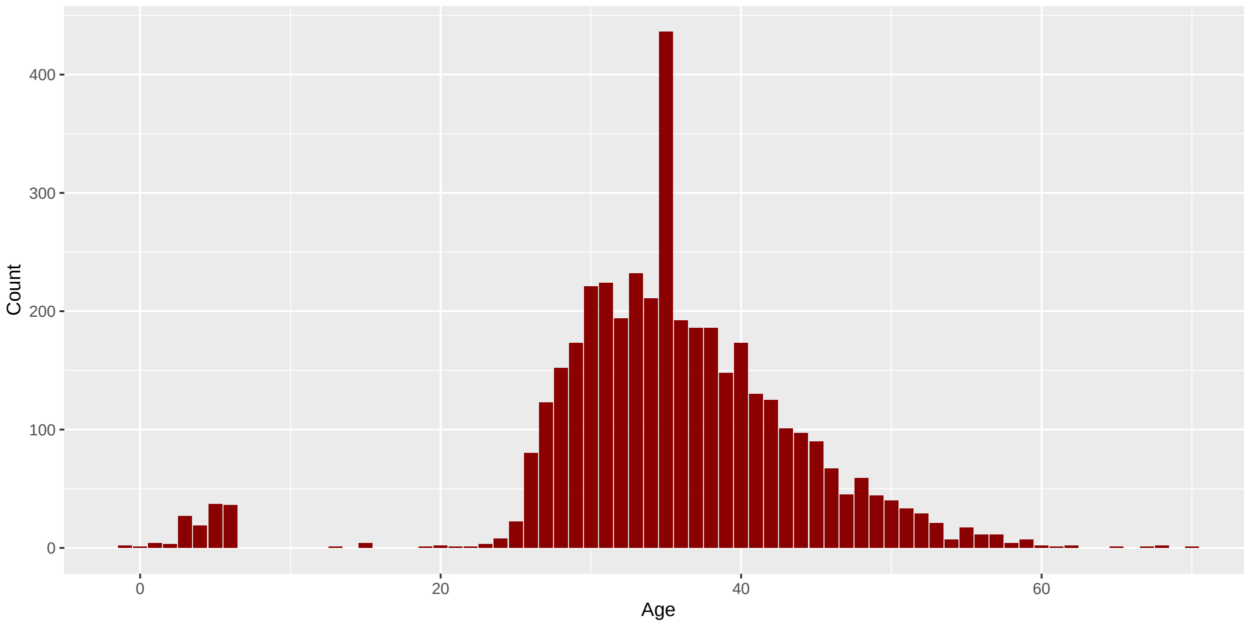
```r
ggplot(aau_desc_online, aes(x=as.factor(gender), fill = as.factor(gender))) +
  geom_bar() + xlab("Gender") + ylab("Count") +
  scale_fill_manual(values = c("goldenrod", "darkred"))
```


Count
600
400
200
0
0
1
Gender
as.factor(gender)
0
1

Age

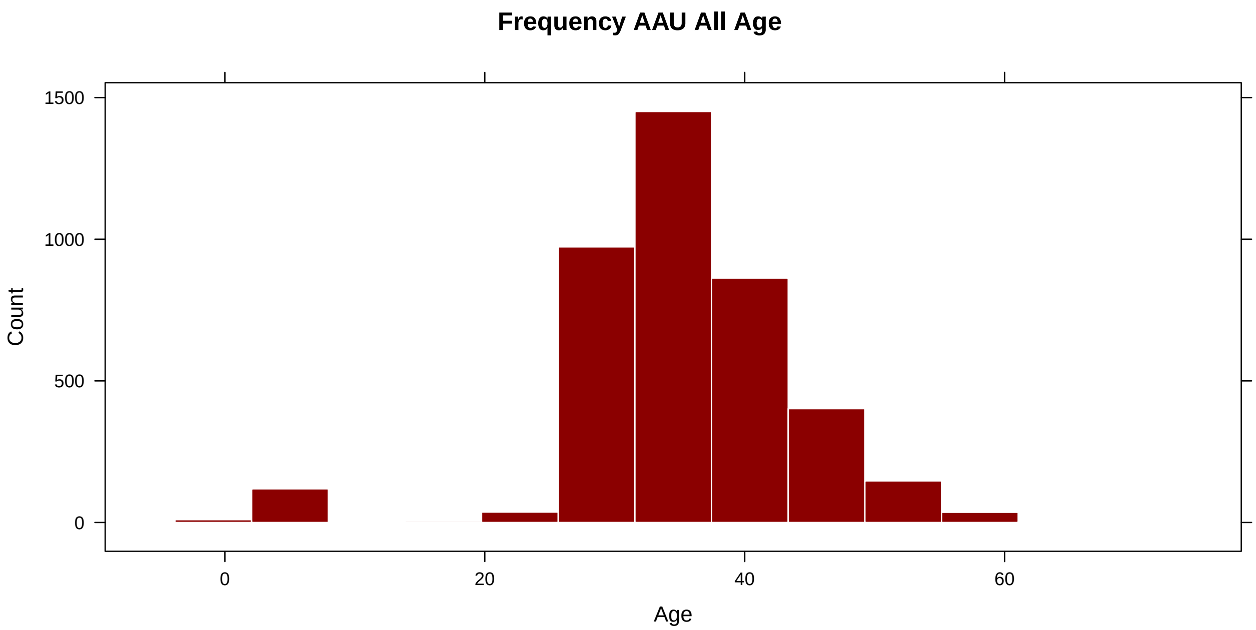
AAU Dataset - Frequency

```
ggplot(aau_desc_all, aes(x=age)) +
  geom_bar(fill="darkred") + xlab("Age") + ylab("Count")
```



AAU Dataset - Histogram

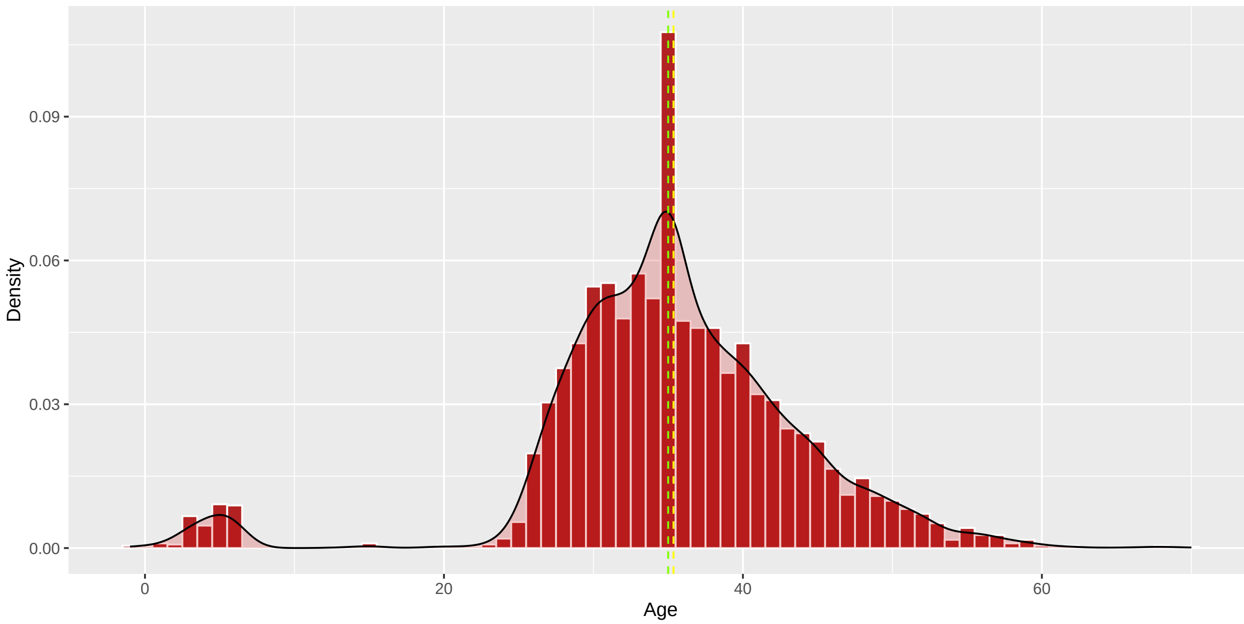
```
histogram(aau_desc_all$age,
          type = "count", main='Frequency AAU All Age', xlab='Age',
          col='darkred', border = "white")
```



AAU Dataset - Histogram with Density

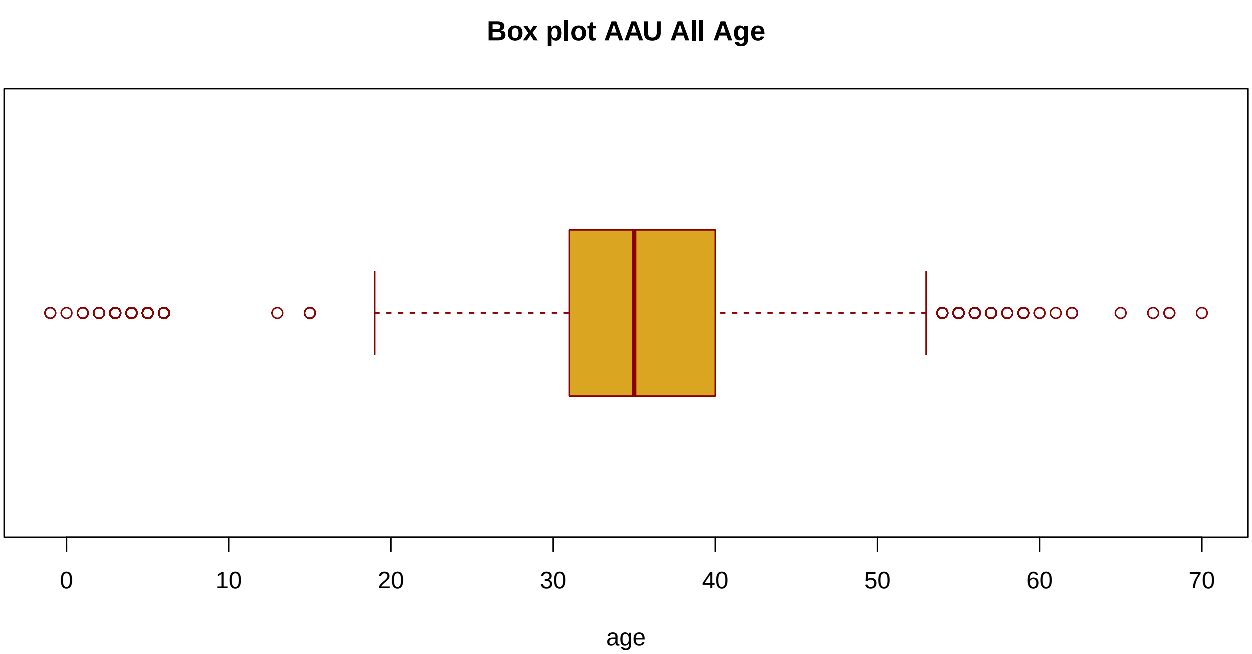
```
ggplot(aau_desc_all, aes(x=age)) +
 geom_histogram(aes(y=..density..),  binwidth= 1, colour="white", fill="firebrick") +
 geom_density(alpha=.2, fill="red3") +
geom_vline(aes(xintercept=mean(age)),color="yellow", linetype="dashed") +
  geom_vline(aes(xintercept=median(age)), color="chartreuse", linetype="dashed") +
  labs(x="Age", y="Density")
```

```
## Warning: The dot-dot notation (`..density..`) was deprecated in ggplot2 3.4.0.
## i Please use `after_stat(density)` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```



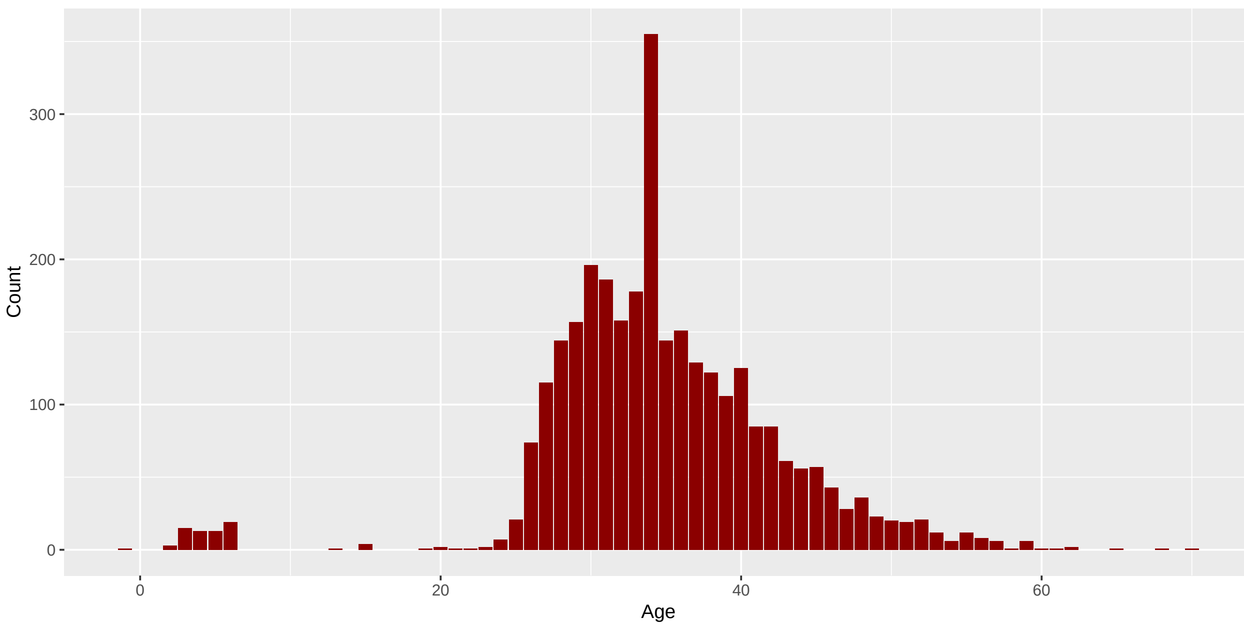
AAU Dataset - Box plot

```
boxplot(aau_desc_all$age,
main = "Box plot AAU All Age", xlab = "age", col = "goldenrod", border = "darkred",
horizontal = TRUE, notch = FALSE)
```



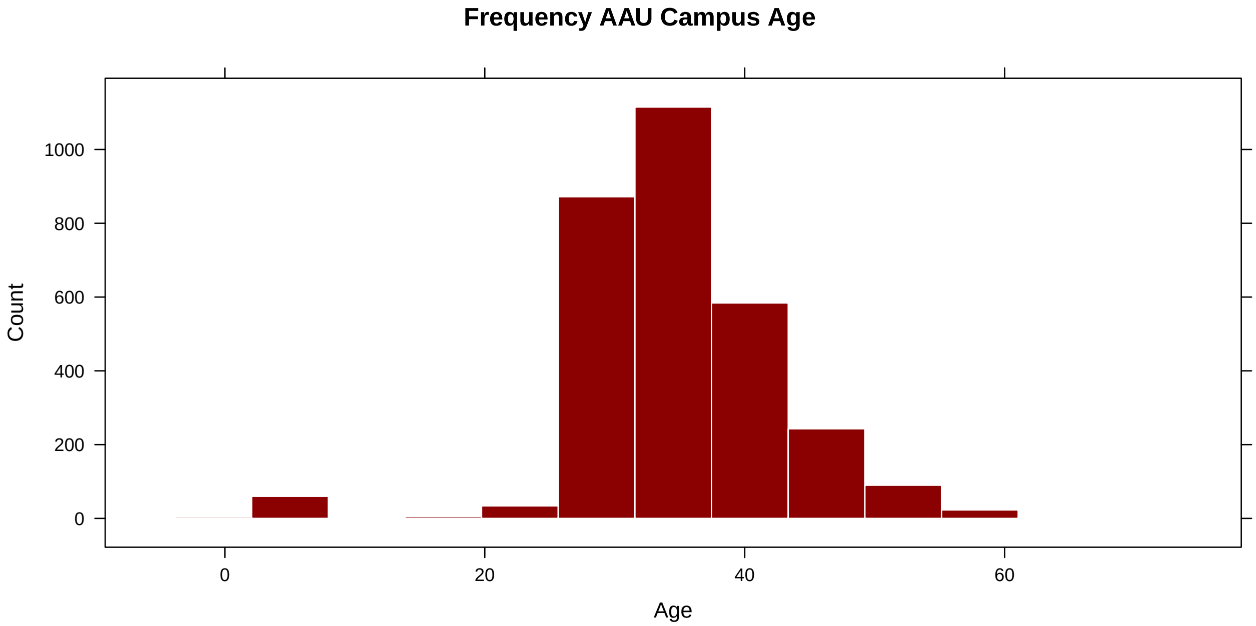
AAU Campus - Frequency

```
ggplot(aau_desc_campus, aes(age)) + xlab("Age") + ylab("Count") +
  geom_bar(fill = "darkred")
```



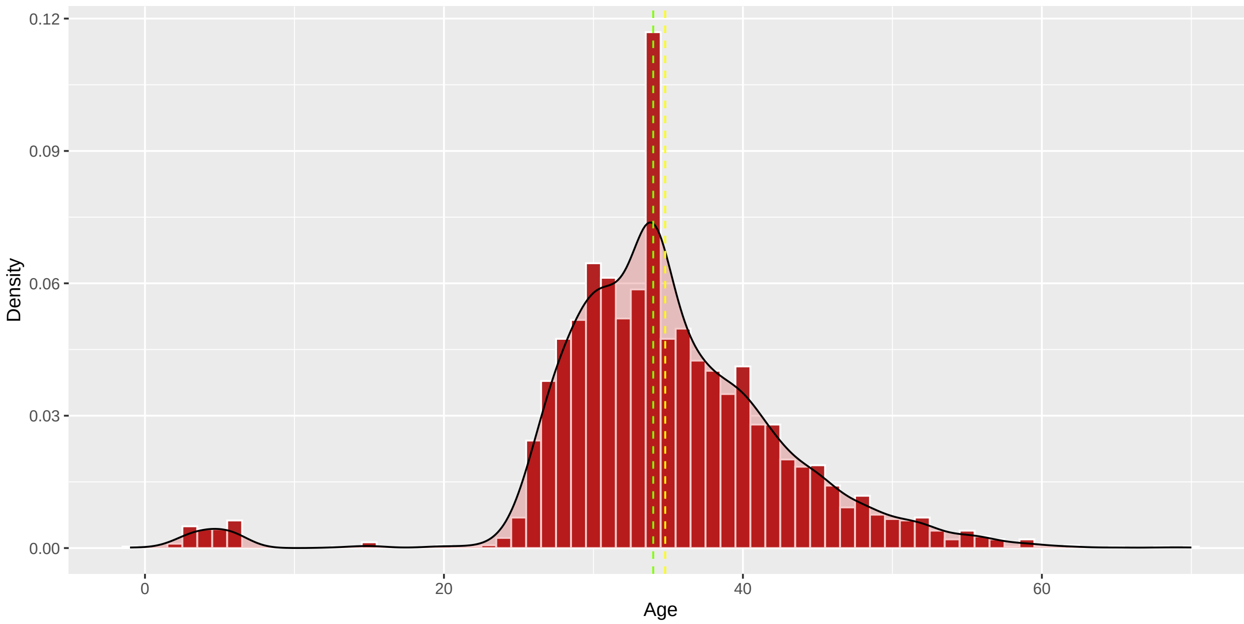
AAU Campus - Histogram

```
histogram(aau_desc_campus$age,
          type = "count", main='Frequency AAU Campus Age', xlab='Age',
          col='darkred', border = "white")
```



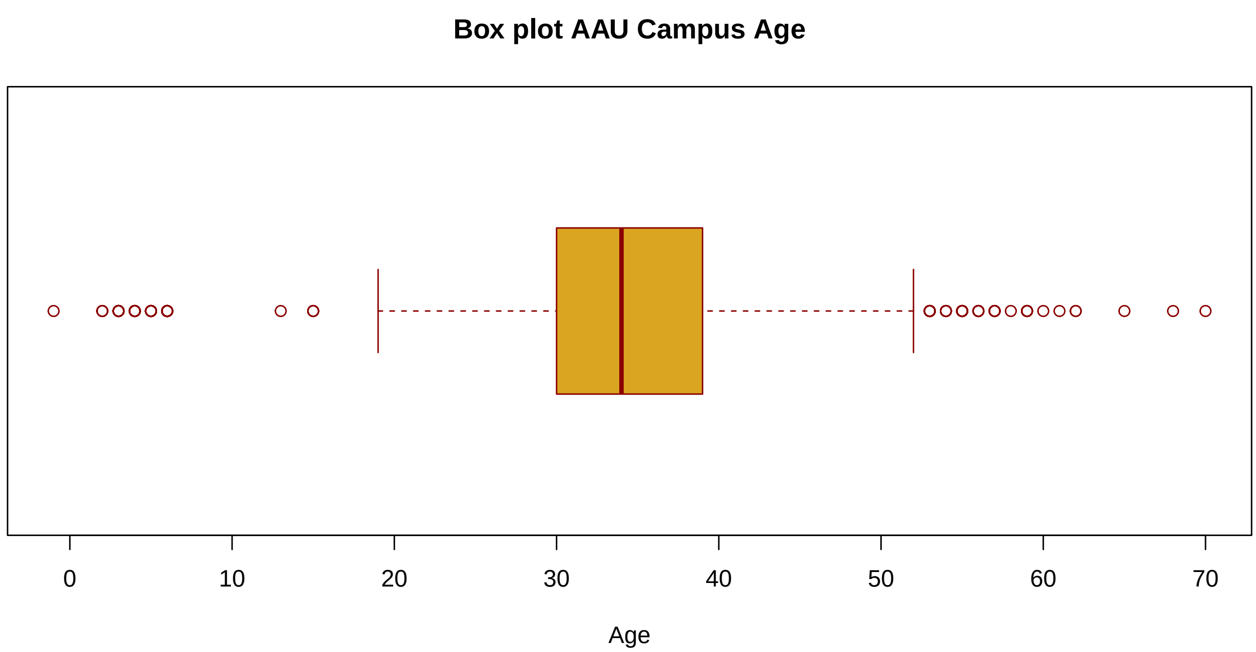
AAU Campus - Historgram with density

```
ggplot(aau_desc_campus, aes(x=age)) +
 geom_histogram(aes(y=..density..), binwidth= 1, colour="white", fill="firebrick")+
 geom_density(alpha=.2, fill="red3") +
geom_vline(aes(xintercept=mean(age)), color="yellow", linetype="dashed") +
geom_vline(aes(xintercept=median(age)), color="chartreuse", linetype="dashed") +
labs(x="Age", y="Density")
```



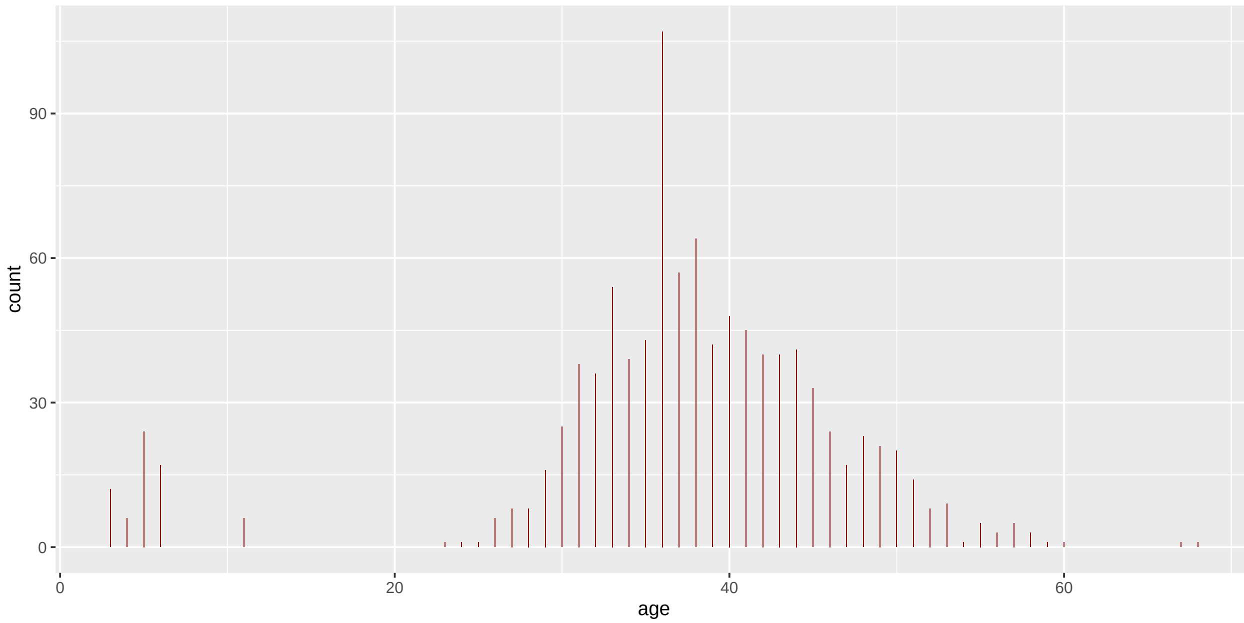
AAU Campus - Box plot

```
boxplot(aau_desc_campus$age,
main = "Box plot AAU Campus Age", xlab = "Age", col = "goldenrod", border = "darkred",
horizontal = TRUE, notch = FALSE)
```



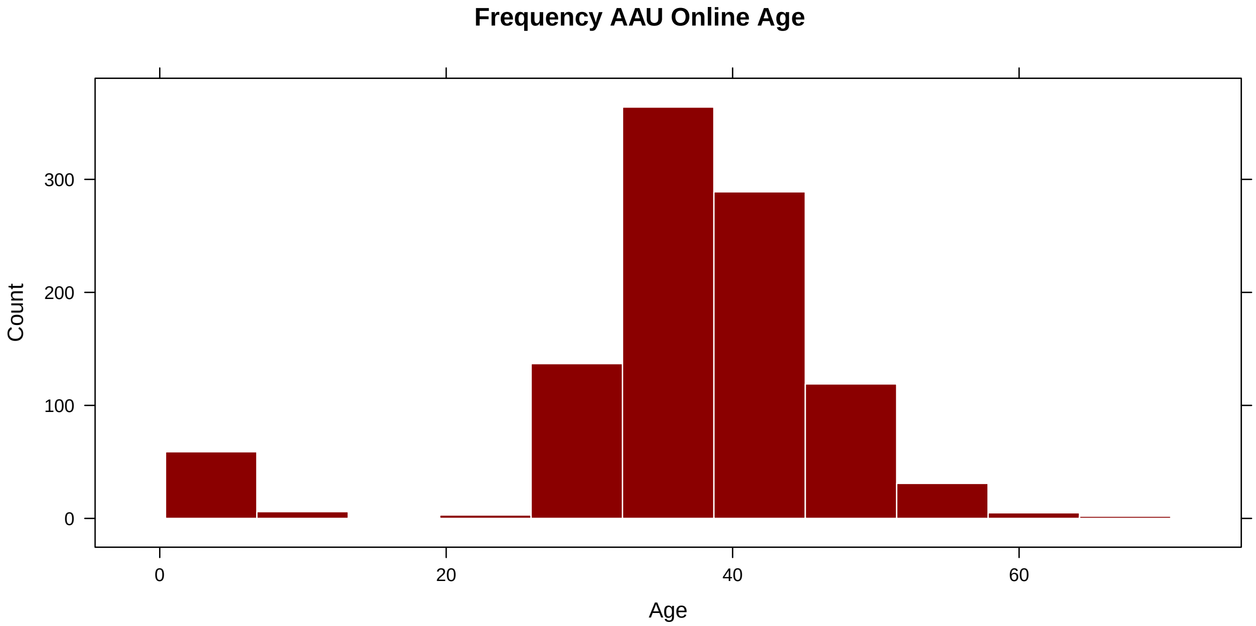
AAU Online - Frequency

```
ggplot(aau_desc_online, aes(age)) + geom_bar(fill = "darkred", width = .04)
```



***AAU Online - Historigram"**

```
histogram(aau_desc_online$age,
          type = "count", main='Frequency AAU Online Age', xlab='Age', col='darkred',
          border = "white")
```

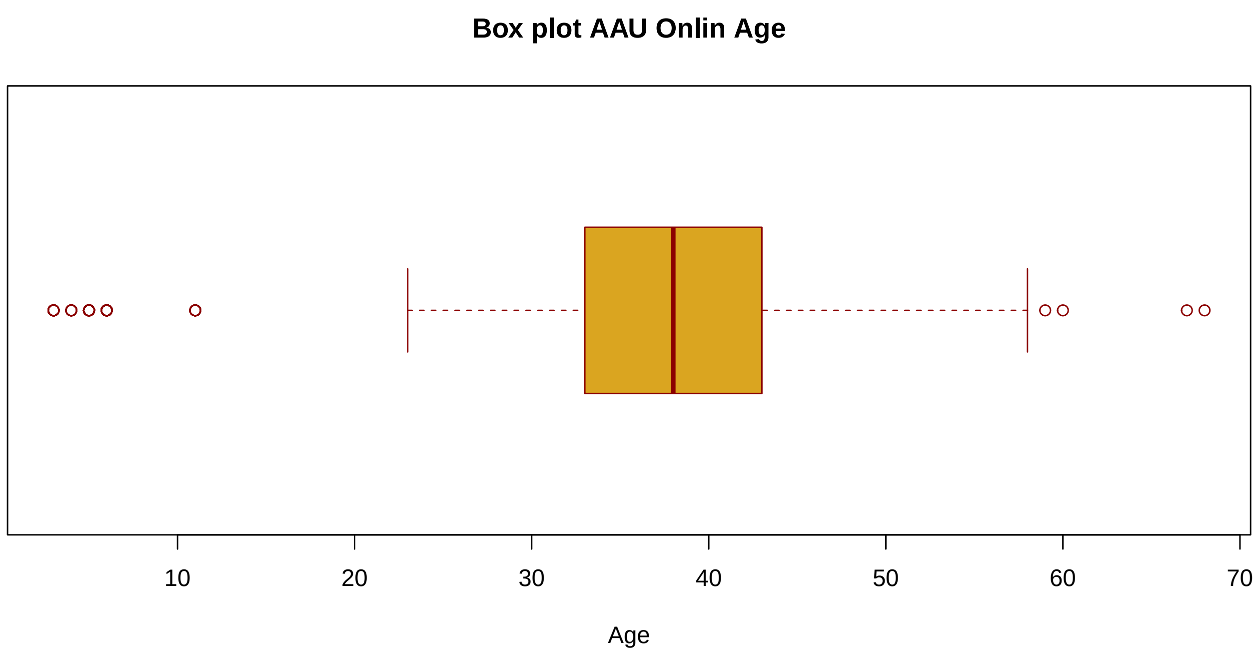


AAU Online - Histogram with density

```
ggplot(aau_desc_online, aes(x=age)) +
 geom_histogram(aes(y=..density..), binwidth= 1, colour="white", fill="firebrick")+
 geom_density(alpha=.2, fill="red3") +
geom_vline(aes(xintercept=mean(age)), color="yellow", linetype="dashed") +
  geom_vline(aes(xintercept=median(age)), color="chartreuse", linetype="dashed") +
  labs(x="Age", y="Density")
```

AAU Online - Box plot

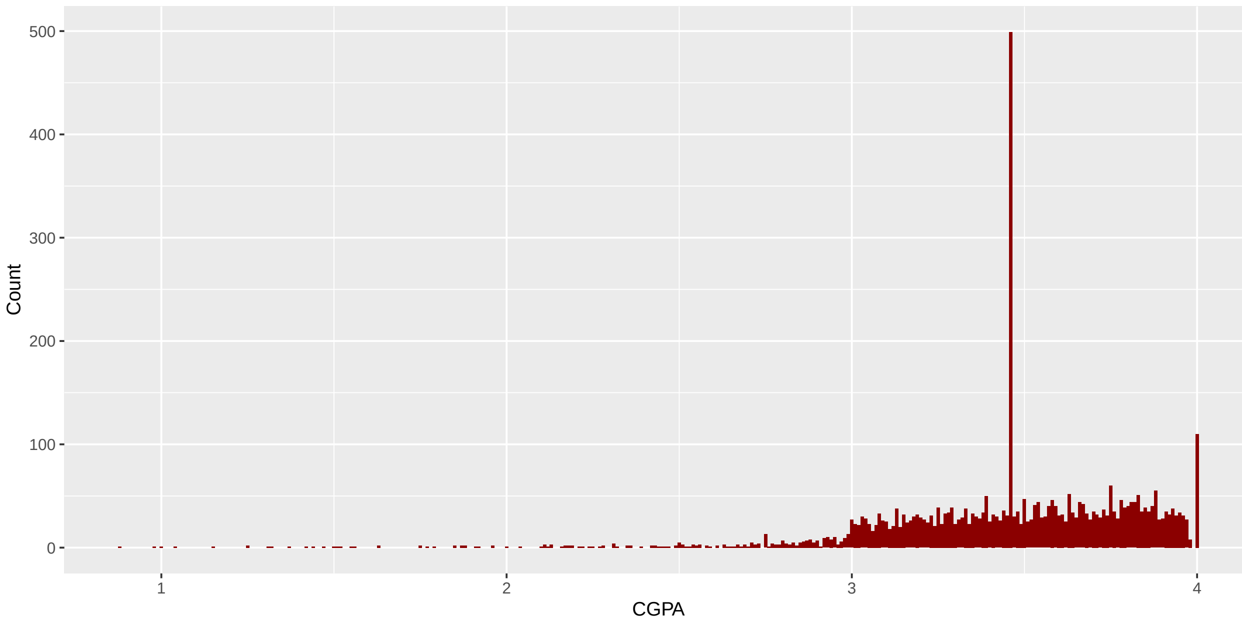
```
boxplot(aau_desc_online$age,
main = "Box plot AAU Onlin Age", xlab = "Age", col = "goldenrod", border = "darkred",
horizontal = TRUE, notch = FALSE)
```



CGPA

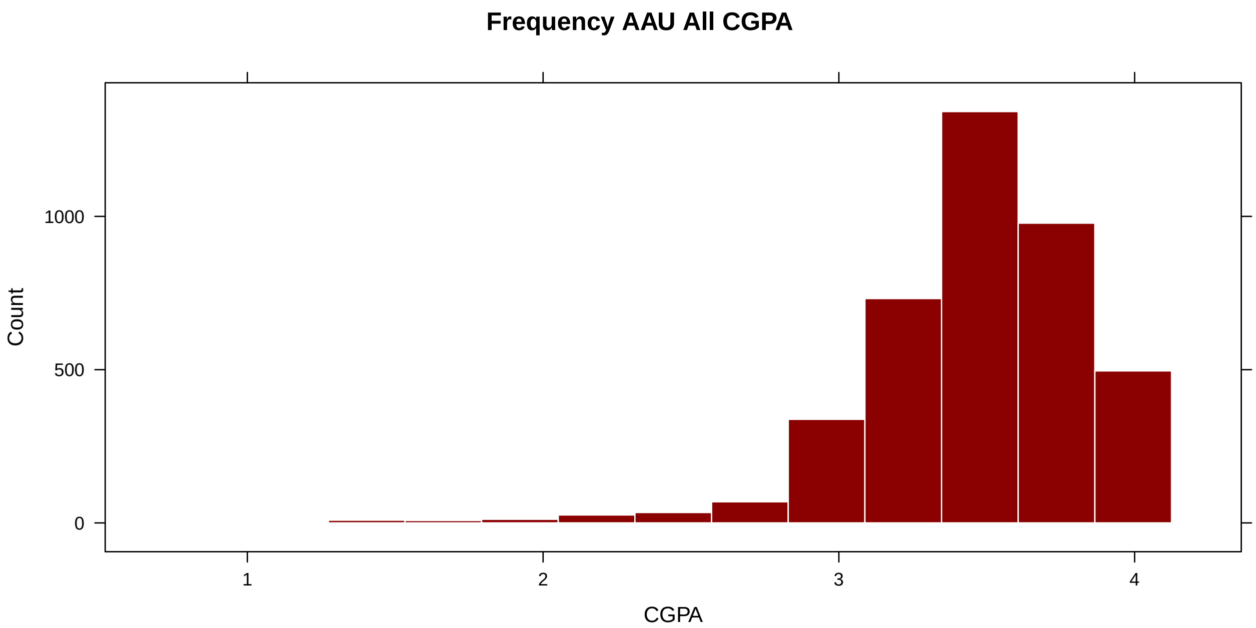
AAU Dataset - Frequency

```
ggplot(aau_desc_all, aes(cgpa)) + geom_bar(fill = "darkred") +
   xlab("CGPA") + ylab("Count")
```



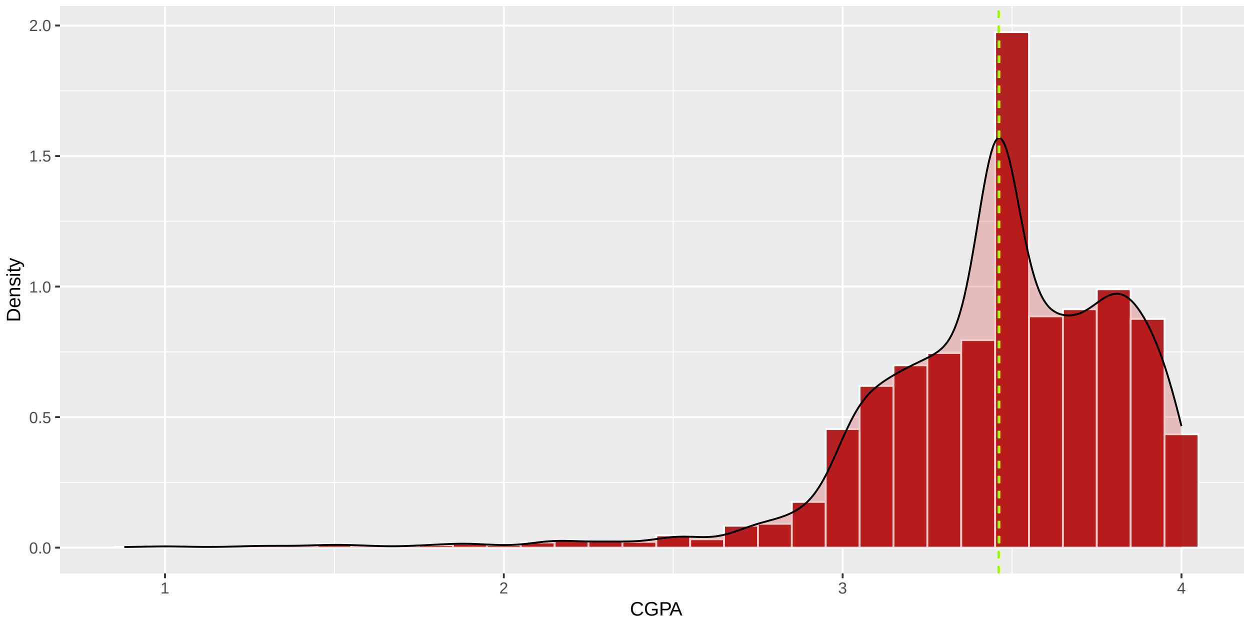
AAU Dataset - Histogram

```
histogram(aau_desc_all$cgpa,
          type = "count", main='Frequency AAU All CGPA',  xlab='CGPA',
          col='darkred', border = "white")
```



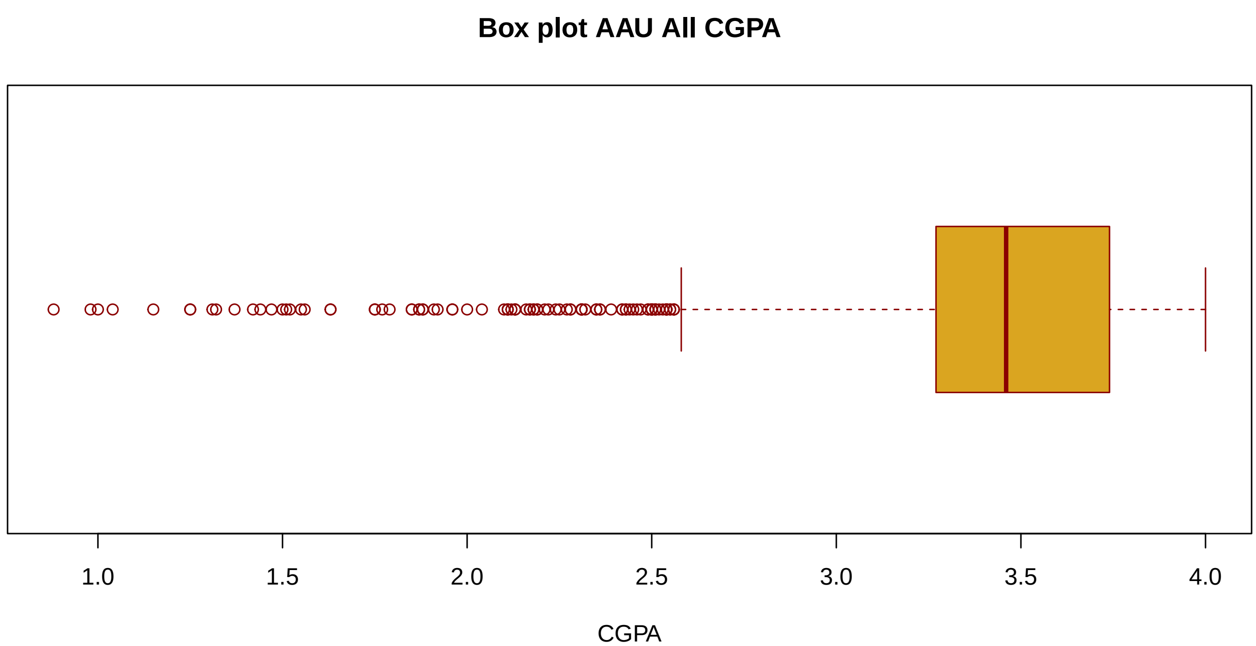
AAU Dataset - Histogram with density

```
ggplot(aau_desc_all, aes(x=cgpa)) +
 geom_histogram(aes(y=..density..), binwidth= .10, colour="white", fill="firebrick")+
 geom_density(alpha=.2, fill="red3") +
geom_vline(aes(xintercept=mean(cgpa)), color="yellow", linetype="dashed") +
  geom_vline(aes(xintercept=median(cgpa)), color="chartreuse", linetype="dashed") +
  labs(x="CGPA", y="Density")
```



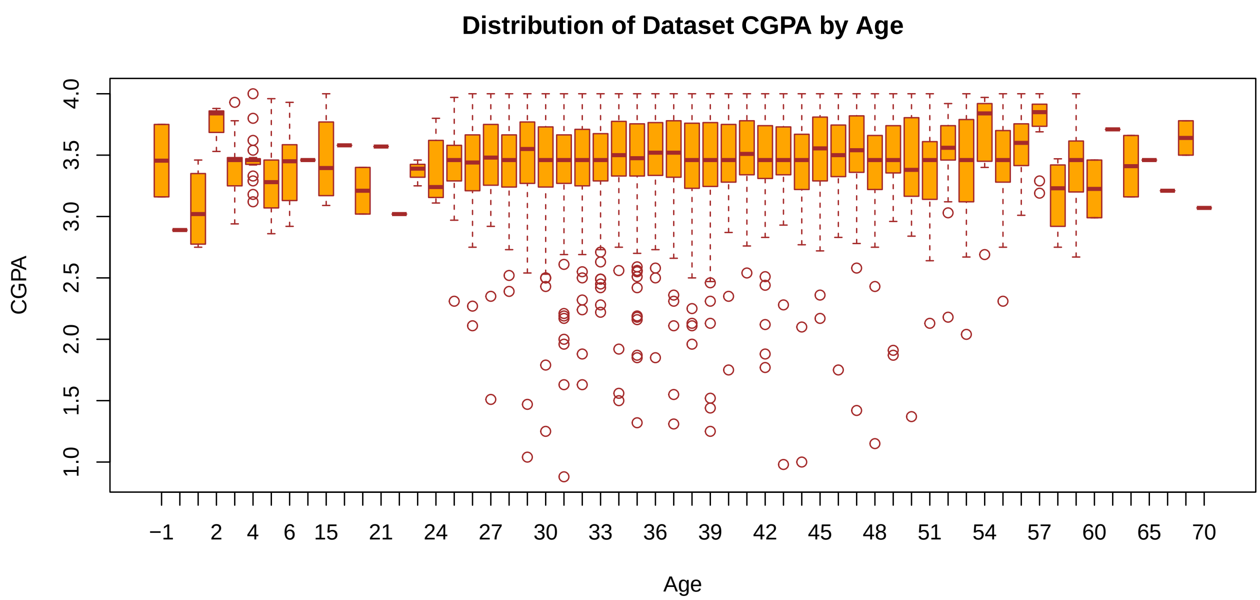
AAU Dataset - Box plot

```
boxplot(aau_desc_all$cgpa,
main = "Box plot AAU All CGPA", xlab = "CGPA", col = "goldenrod", border = "darkred",
horizontal = TRUE, notch = FALSE)
```



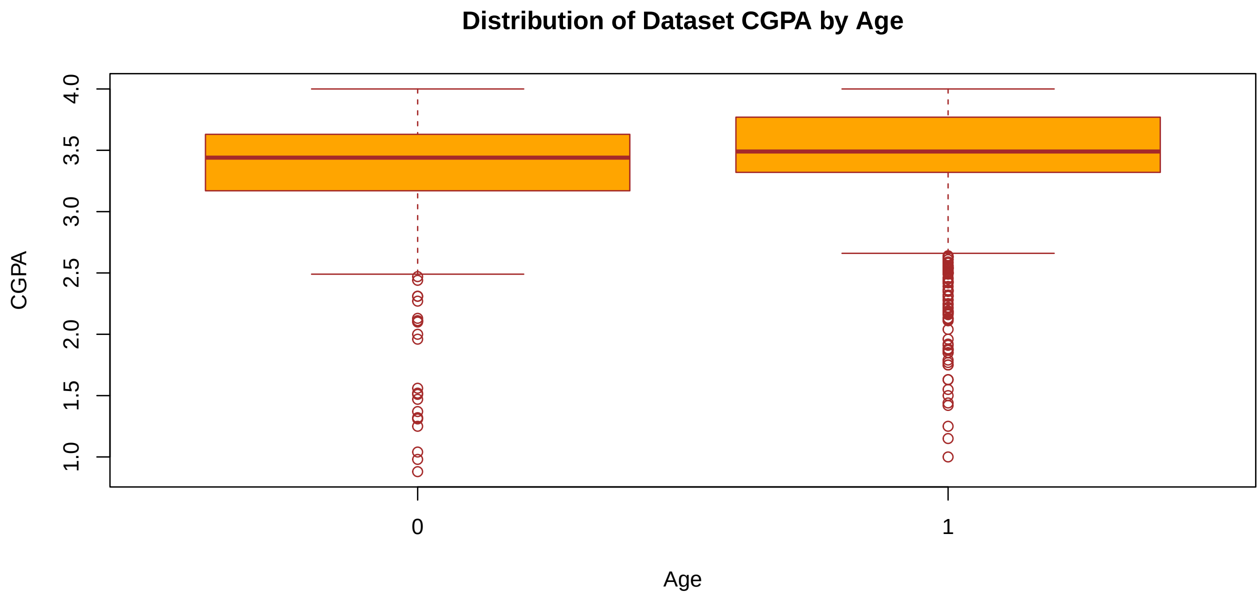
**AAU Dataset - Box plot (CGPA by Age)*

```
boxplot(cgpa~age,
data=aau_desc_all,
main="Distribution of Dataset CGPA by Age", xlab="Age", ylab="CGPA", col="orange",
border="brown")
```



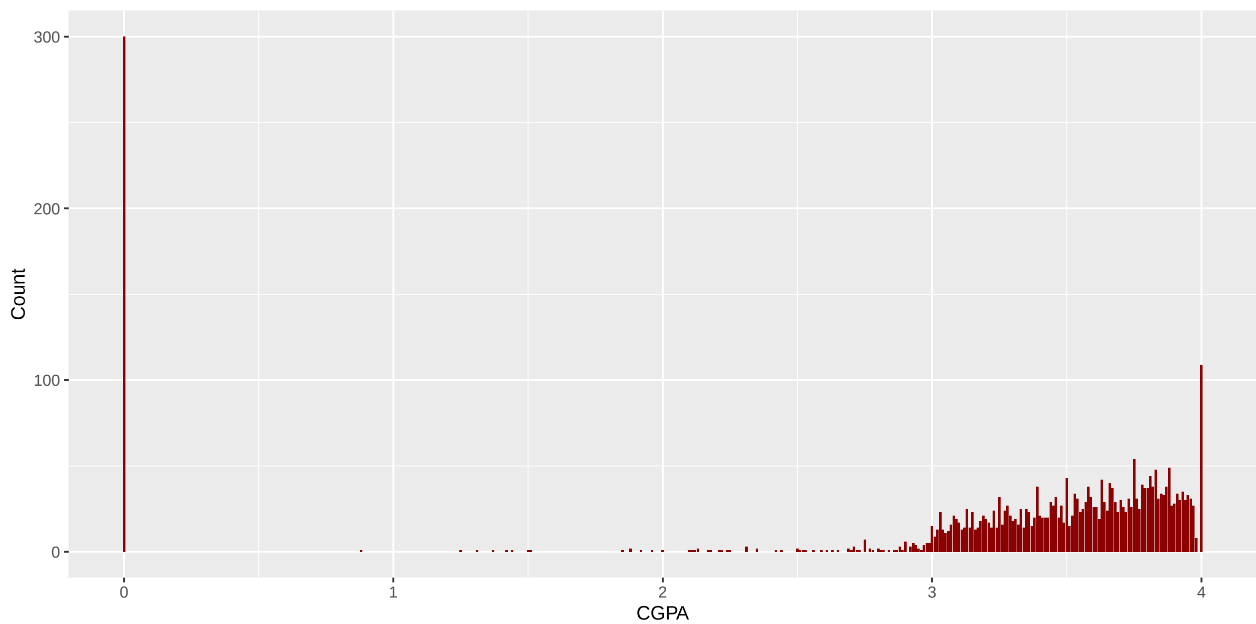
**AAU Dataset - Box plot (CGPA by Gender)*

```
boxplot(cgpa~gender,
data=aau_desc_all,
main="Distribution of Dataset CGPA by Age", xlab="Age", ylab="CGPA", col="orange",
border="brown")
```



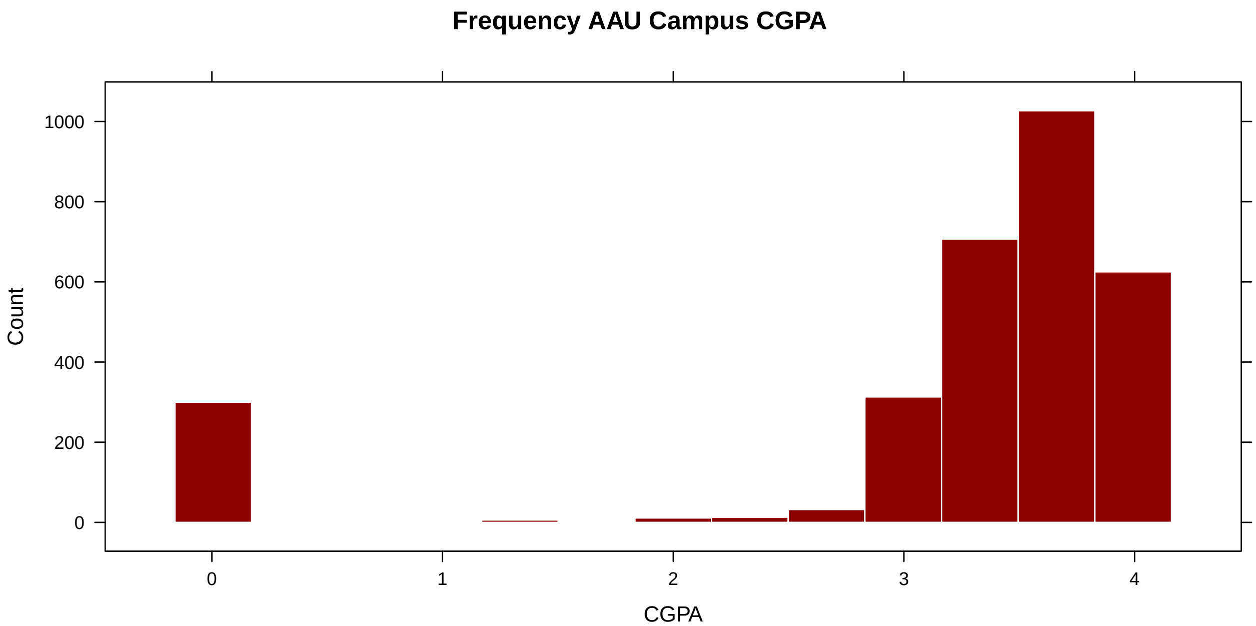
AAU Campus - Frequency

```
ggplot(aau_desc_campus, aes(cgpa)) + xlab("CGPA") + ylab("Count") +
  geom_bar(fill = "darkred")
```



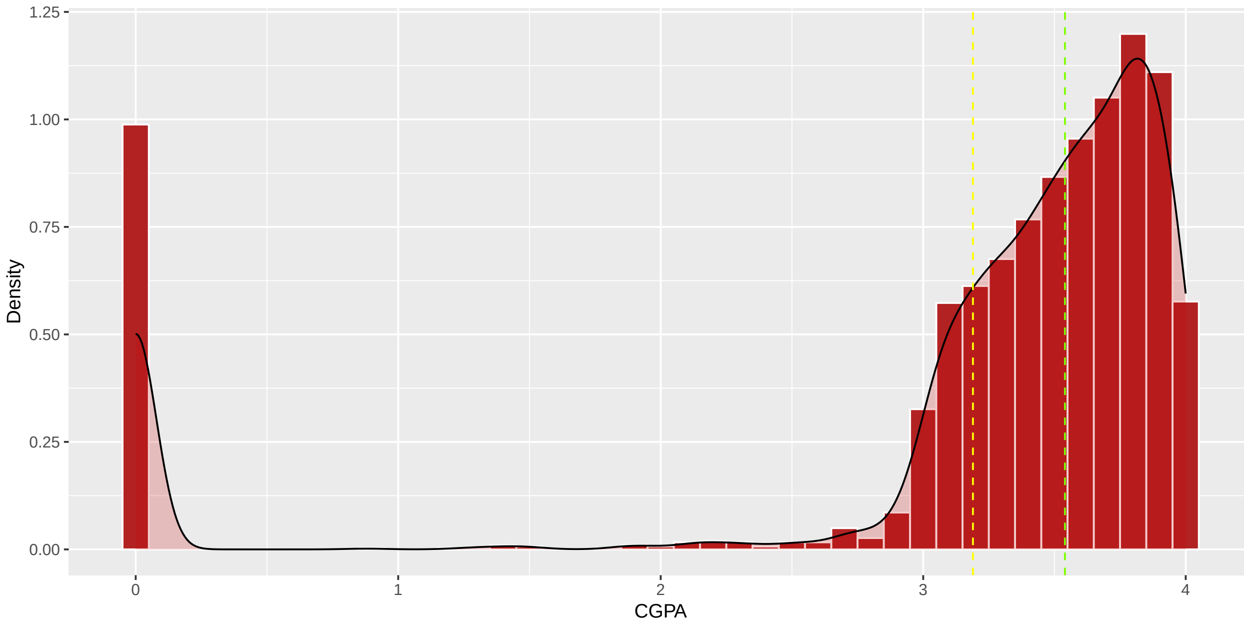
AAU Campus - Histogram

```
histogram(aau_desc_campus$cgpa,
          type = "count", main='Frequency AAU Campus CGPA', xlab='CGPA',
          col='darkred', border = "white")
```



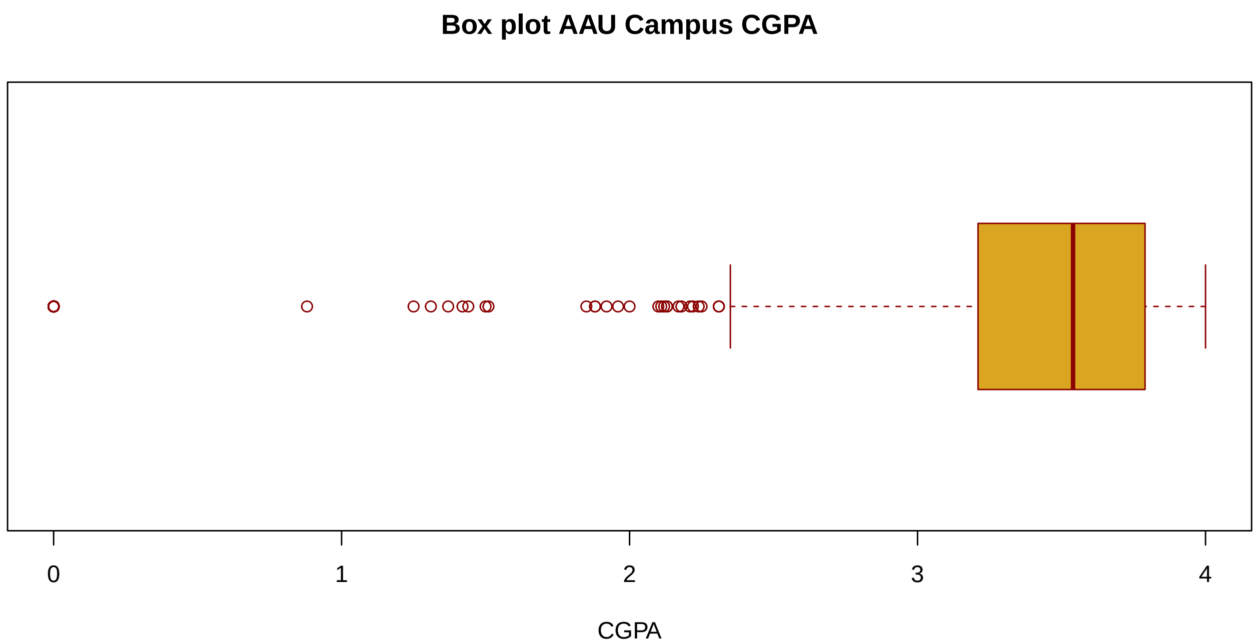
AAU Campus - Histogram with density

```
ggplot(aau_desc_campus, aes(x=cgpa)) +
 geom_histogram(aes(y=..density..), binwidth= .10, colour="white", fill="firebrick")+
 geom_density(alpha=.2, fill="red3") +
geom_vline(aes(xintercept=mean(cgpa)), color="yellow", linetype="dashed") +
geom_vline(aes(xintercept=median(cgpa)), color="chartreuse", linetype="dashed") +
labs(x="CGPA", y="Density")
```



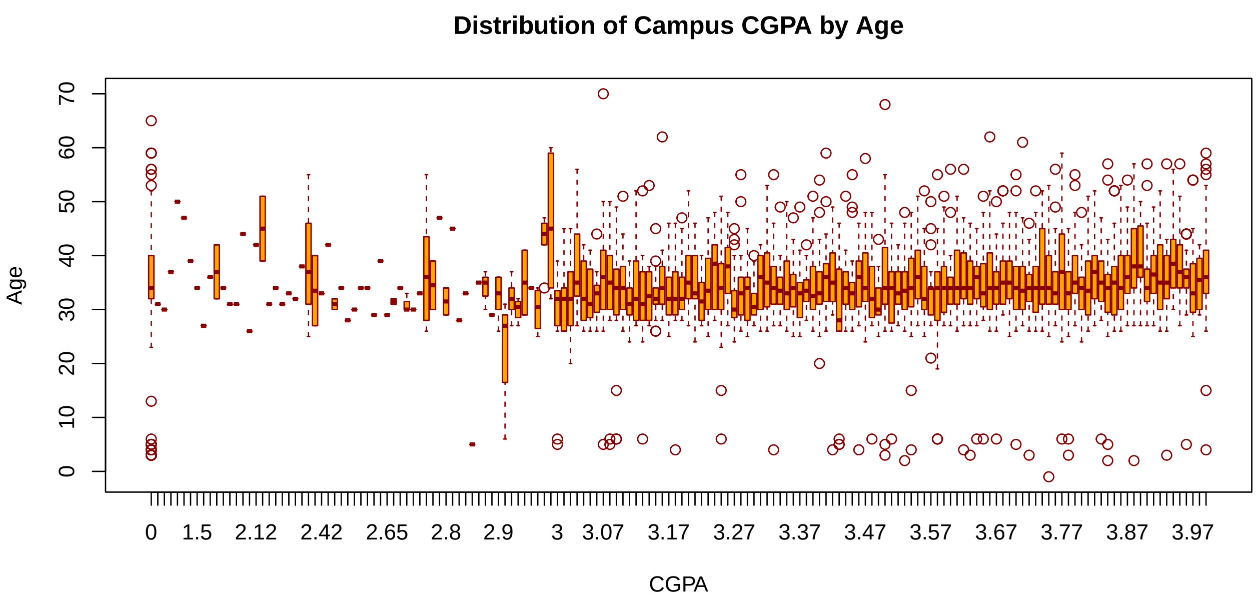
AAU Campus - Box plot

```
boxplot(aau_desc_campus$cgpa,
main = "Box plot AAU Campus CGPA", xlab = "CGPA", col = "goldenrod", border = "darkred",
horizontal = TRUE, notch = FALSE)
```



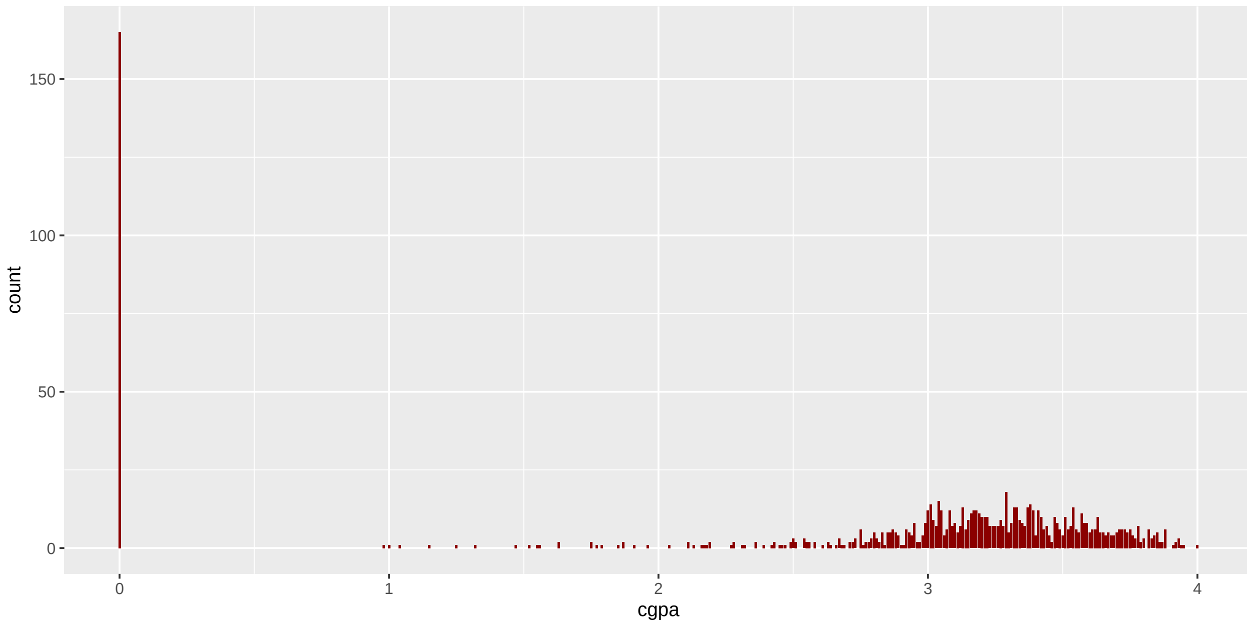
AAU Campus - Box plot (CGPA by Age)

```
boxplot(age~cgpa,
data=aau_desc_campus,
main="Distribution of Campus CGPA by Age", xlab="CGPA", ylab="Age", col="orange",
border="darkred")
```



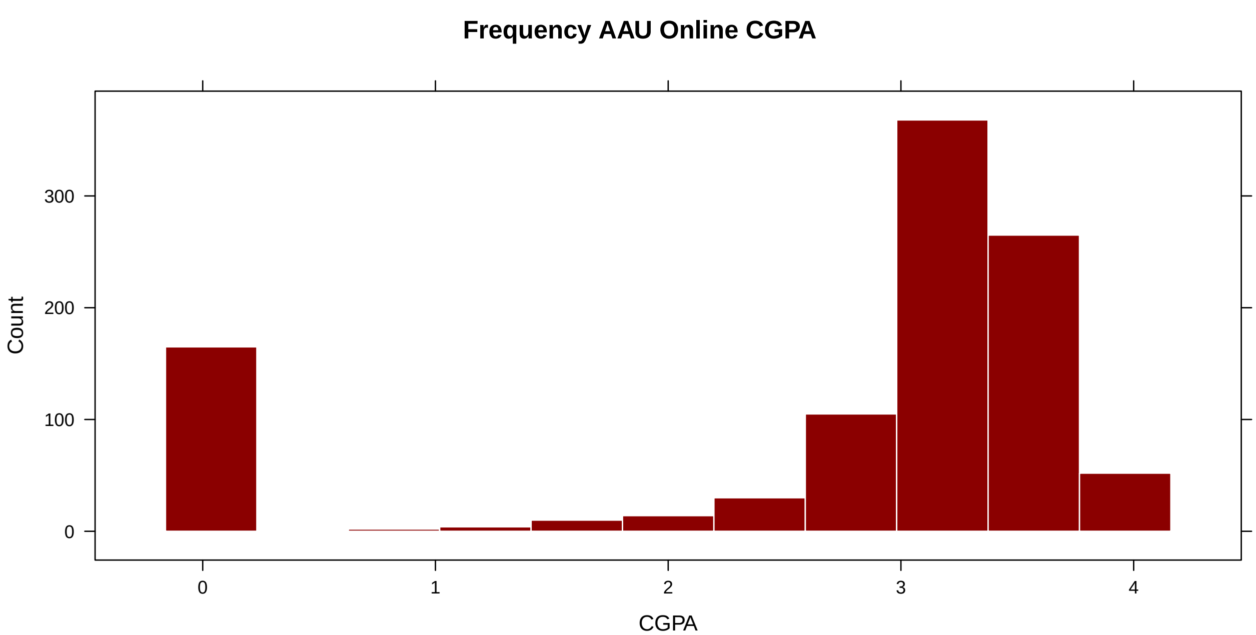
AAU Online - Frquency

```
ggplot(aau_desc_online, aes(cgpa)) + geom_bar(fill = "darkred")
```



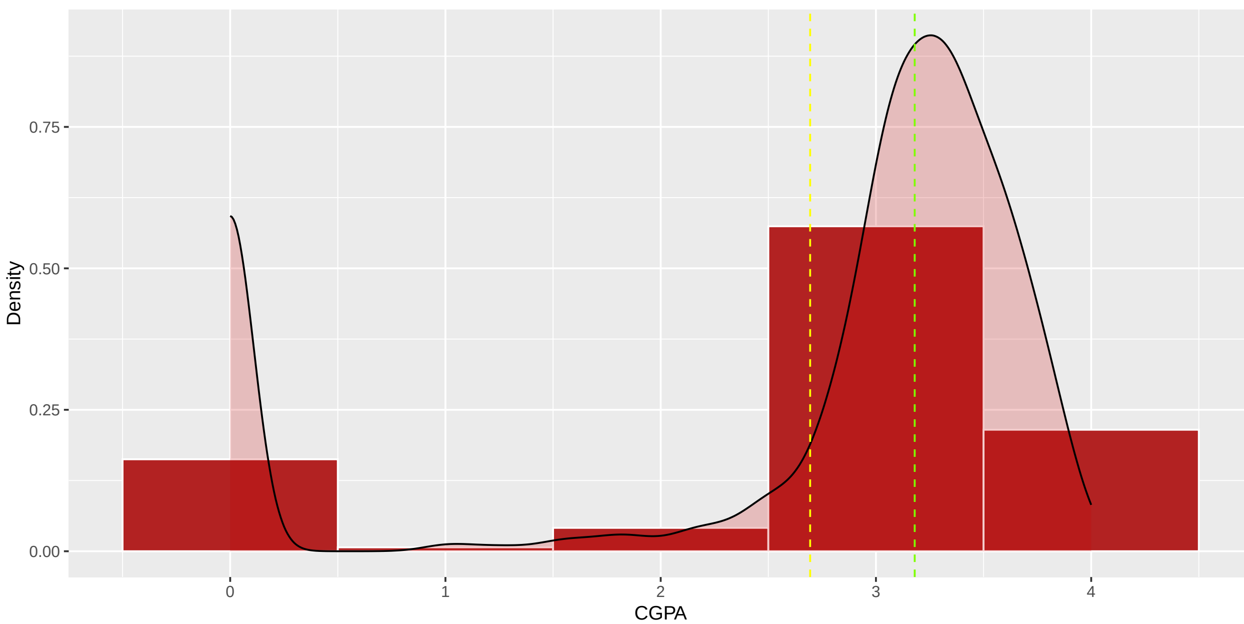
AAU Online - Histogram

```
histogram(aau_desc_online$cgpa,
          type = "count", main='Frequency AAU Online CGPA', xlab='CGPA', col='darkred',
          border = "white")
```



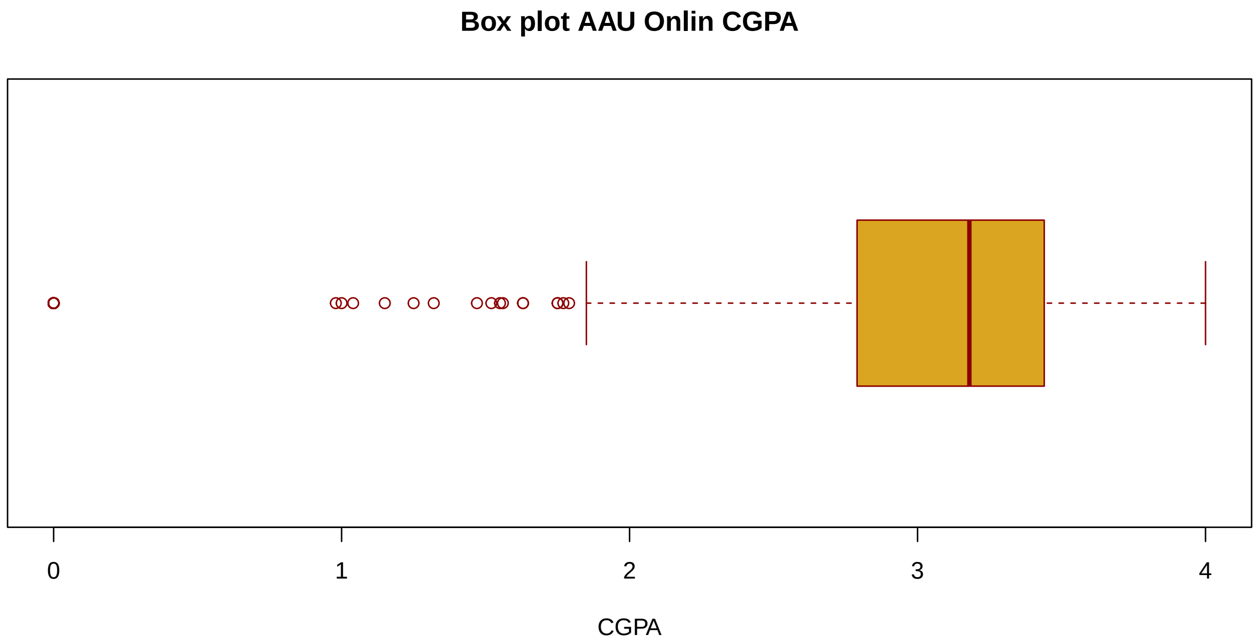
AAU Online - Histogram with density

```
ggplot(aau_desc_online, aes(x=cgpa)) +
 geom_histogram(aes(y=..density..), binwidth= 1, colour="white", fill="firebrick")+
 geom_density(alpha=.2, fill="red3") +
geom_vline(aes(xintercept=mean(cgpa)), color="yellow", linetype="dashed") +
  geom_vline(aes(xintercept=median(cgpa)), color="chartreuse", linetype="dashed") +
  labs(x="CGPA", y="Density")
```



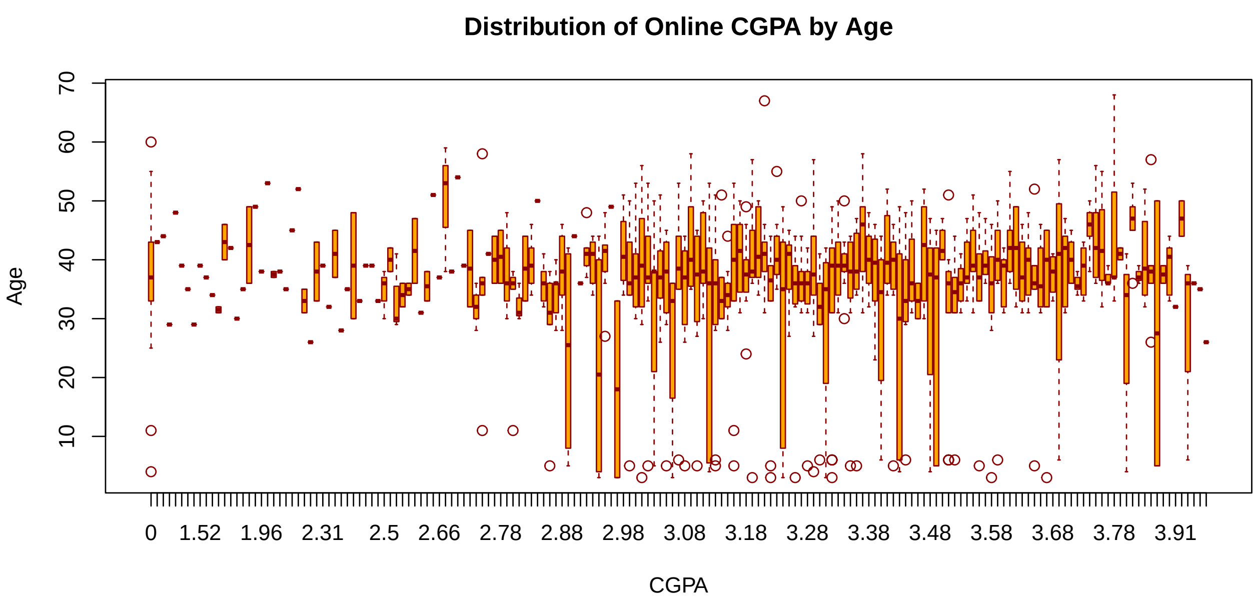
AAU Online - Box plot

```
boxplot(aau_desc_online$cgpa, main = "Box plot AAU Onlin CGPA", xlab = "CGPA",
        col = "goldenrod", border = "darkred", horizontal = TRUE, notch = FALSE)
```



AAU Online - Box plot (CGPA by Age)

```
boxplot(age~cgpa, data=aau_desc_online, main="Distribution of Online CGPA by Age",
xlab="CGPA", ylab="Age", col="orange", border="darkred" )
```



Year/Level

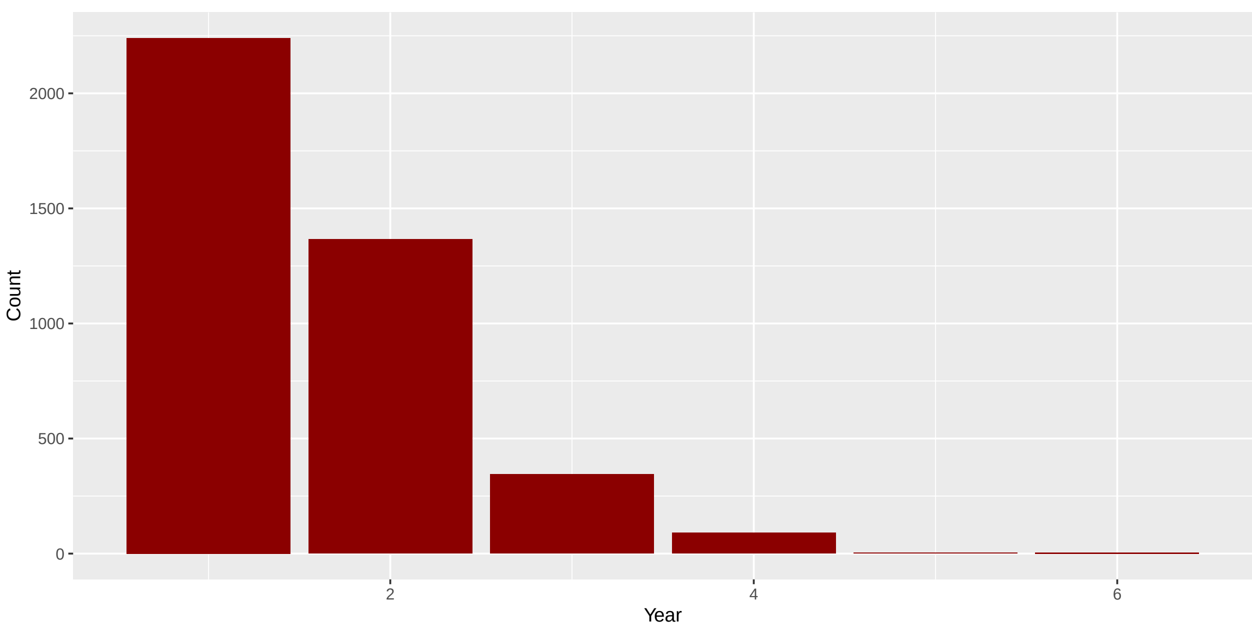
AAU Dataset - Frequency

```r
freq(aau_desc_all$year, plain.ascii = TRUE, style = 'grid')
```

Frequencies
aau_desc_all$year
Type: Numeric

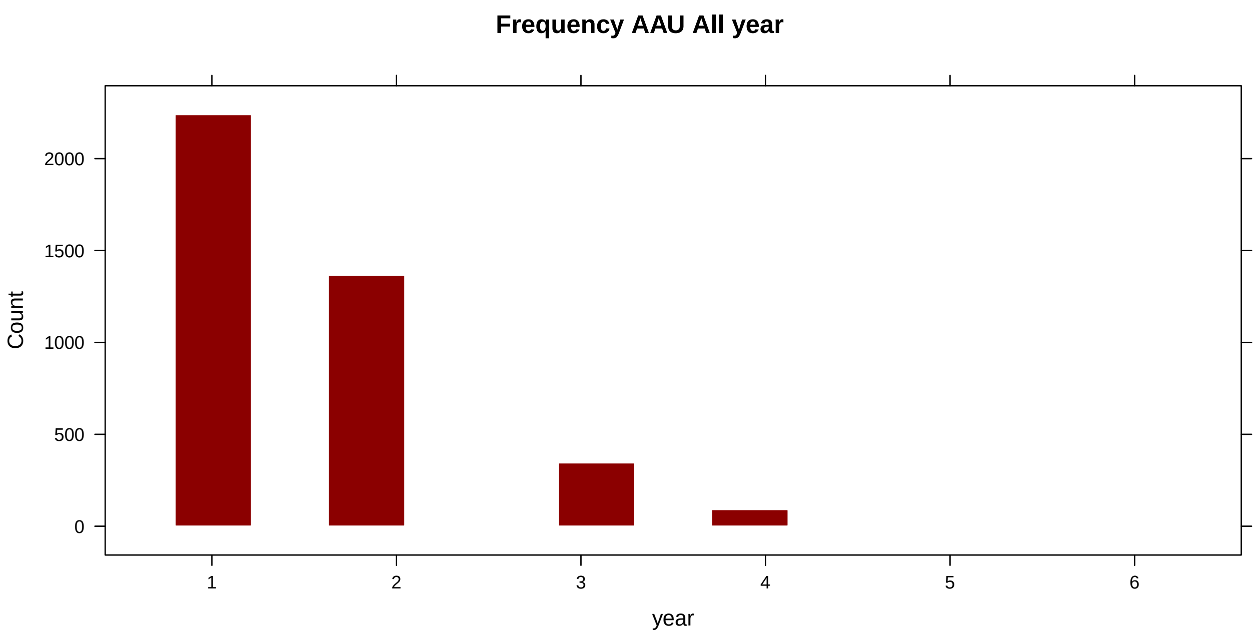
	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
1	2240	55.295	55.295	55.295	55.295
2	1366	33.720	89.015	33.720	89.015
3	345	8.516	97.531	8.516	97.531
4	91	2.246	99.778	2.246	99.778
5	4	0.099	99.877	0.099	99.877
6	5	0.123	100.000	0.123	100.000
<NA>	0			0.000	100.000
Total	4051	100.000	100.000	100.000	100.000

```r
ggplot(aau_desc_all, aes(year)) + xlab("Year") + ylab("Count") +
  geom_bar(fill = "darkred")
```



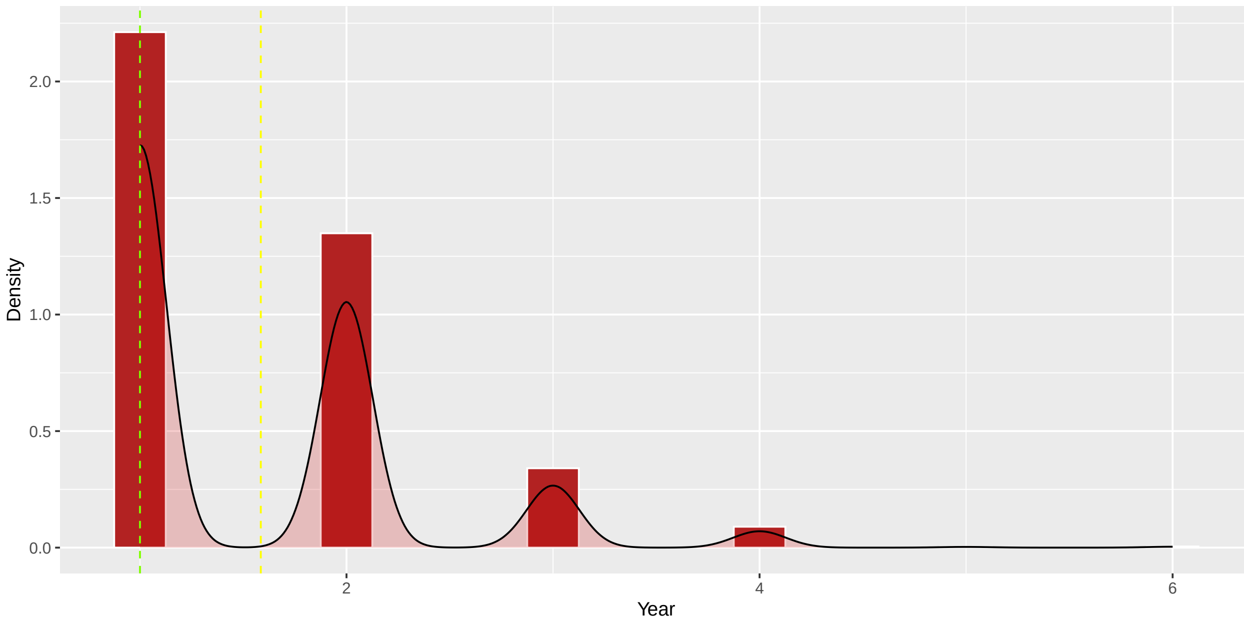
AAU Dataset - Histogram

```
histogram(aau_desc_all$year, type = "count", main='Frequency AAU All year',
          xlab='year', col='darkred', border = "white")
```



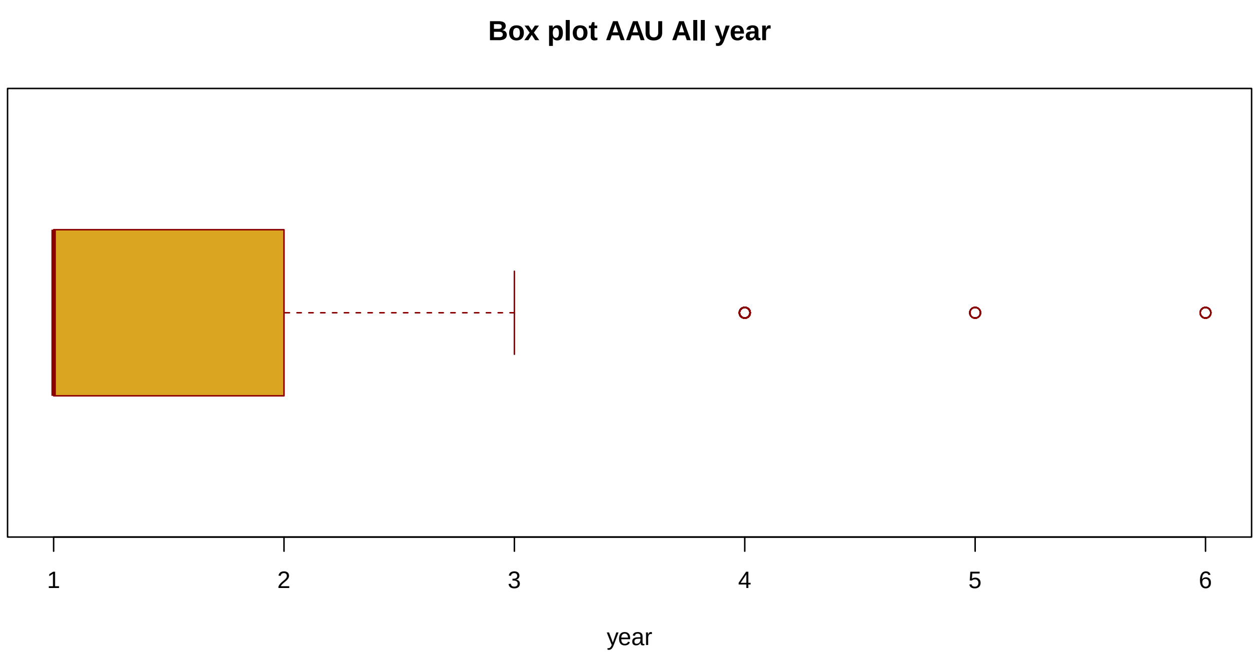
AAU Dataset - Histogram with density

```
ggplot(aau_desc_all, aes(x=year)) +
 geom_histogram(aes(y=..density..), binwidth= .25, colour="white", fill="firebrick")+
 geom_density(alpha=.2, fill="red3") +
geom_vline(aes(xintercept=mean(year)), color="yellow", linetype="dashed") +
  geom_vline(aes(xintercept=median(year)), color="chartreuse", linetype="dashed") +
  labs(x="Year", y="Density")
```



AAU Dataset - Box plot

```
boxplot(aau_desc_all$year, main = "Box plot AAU All year", xlab = "year",
        col = "goldenrod", border = "darkred", horizontal = TRUE, notch = FALSE)
```



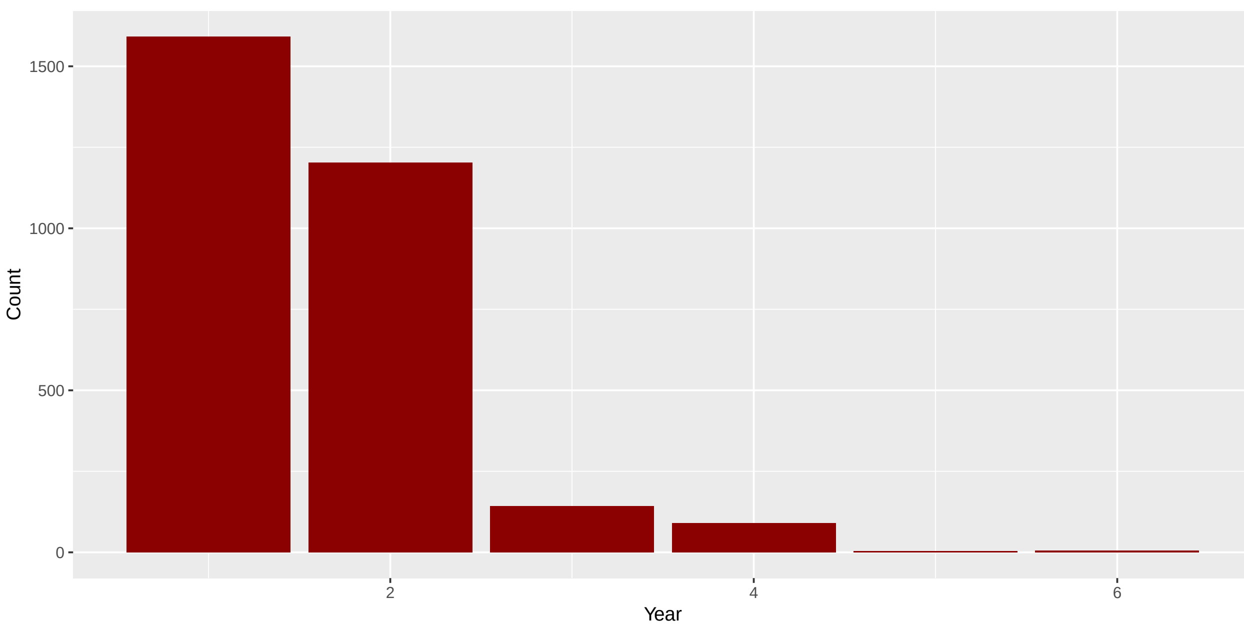
AAU Campus - Frquency

```
freq(aau_desc_campus$year, plain.ascii = TRUE, style = 'grid')
```

Frequencies
aau_desc_campus$year
Type: Numeric

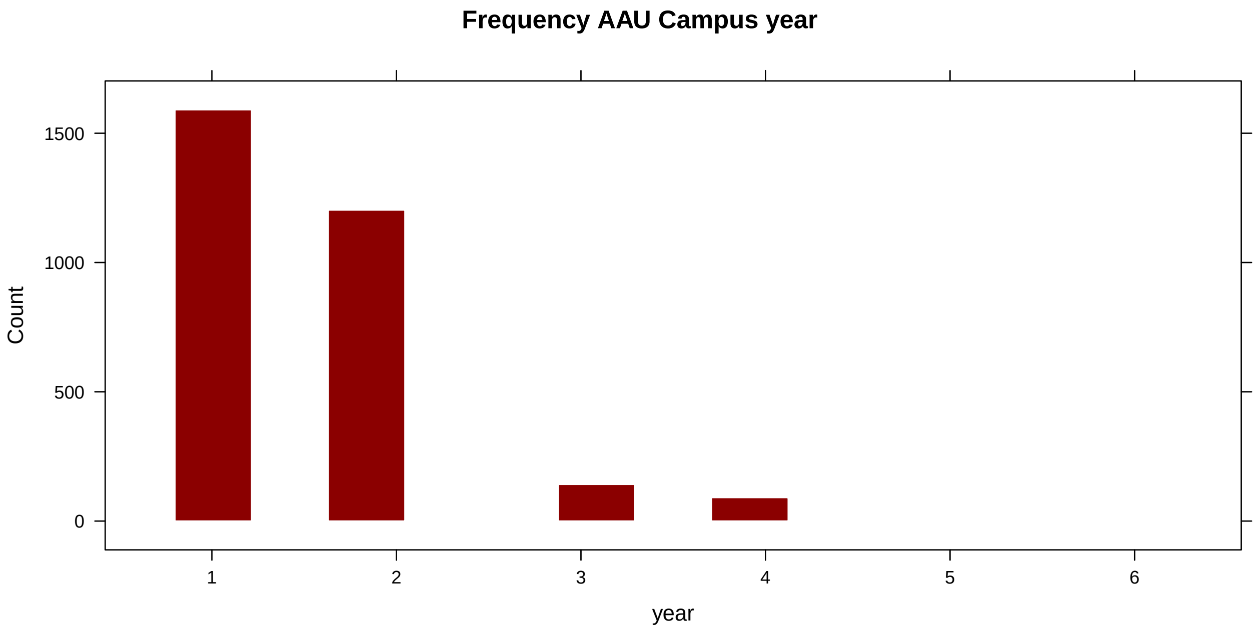
	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
1	1591	52.40	52.40	52.40	52.40
2	1203	39.62	92.03	39.62	92.03
3	142	4.68	96.71	4.68	96.71
4	91	3.00	99.70	3.00	99.70
5	4	0.13	99.84	0.13	99.84
6	5	0.16	100.00	0.16	100.00
<NA>	0			0.00	100.00
Total	3036	100.00	100.00	100.00	100.00

```
ggplot(aau_desc_campus, aes(year)) + xlab("Year") + ylab("Count") +
  geom_bar(fill = "darkred")
```



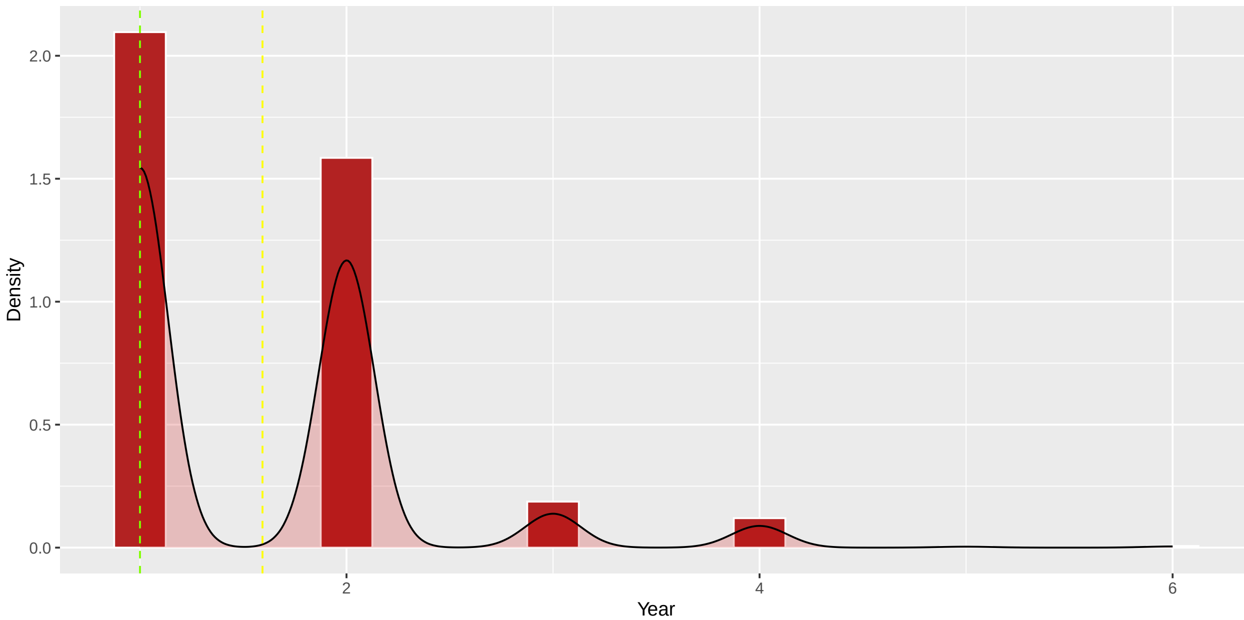
AAU Campus - Histogram

```
histogram(aau_desc_campus$year, type = "count", main='Frequency AAU Campus year',
          xlab='year', col='darkred', border = "white")
```



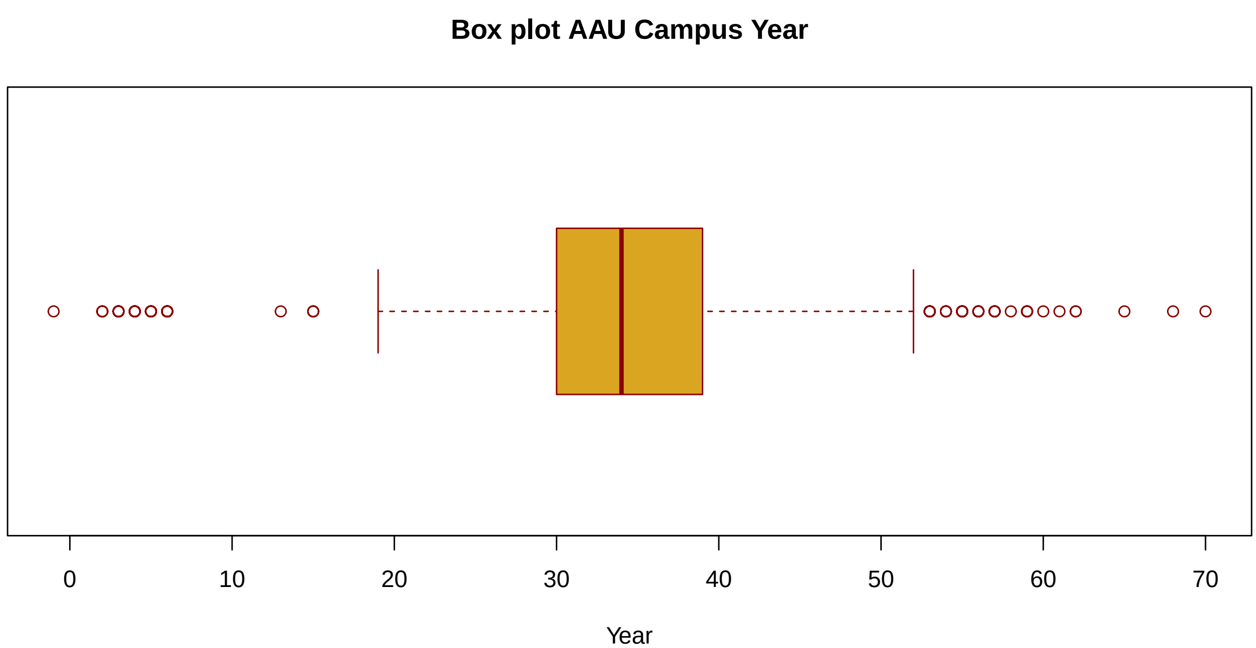
AAU Campus - Histogram with density

```
ggplot(aau_desc_campus, aes(x=year)) +
 geom_histogram(aes(y=..density..), binwidth= .25, colour="white", fill="firebrick")+
 geom_density(alpha=.2, fill="red3") +
geom_vline(aes(xintercept=mean(year)), color="yellow", linetype="dashed") +
  geom_vline(aes(xintercept=median(year)), color="chartreuse", linetype="dashed") +
  labs(x="Year", y="Density")
```



AAU Campus - Box plot

```
boxplot(aau_desc_campus$age, main = "Box plot AAU Campus Year", xlab = "Year",
col = "goldenrod", border = "darkred", horizontal = TRUE, notch = FALSE)
```



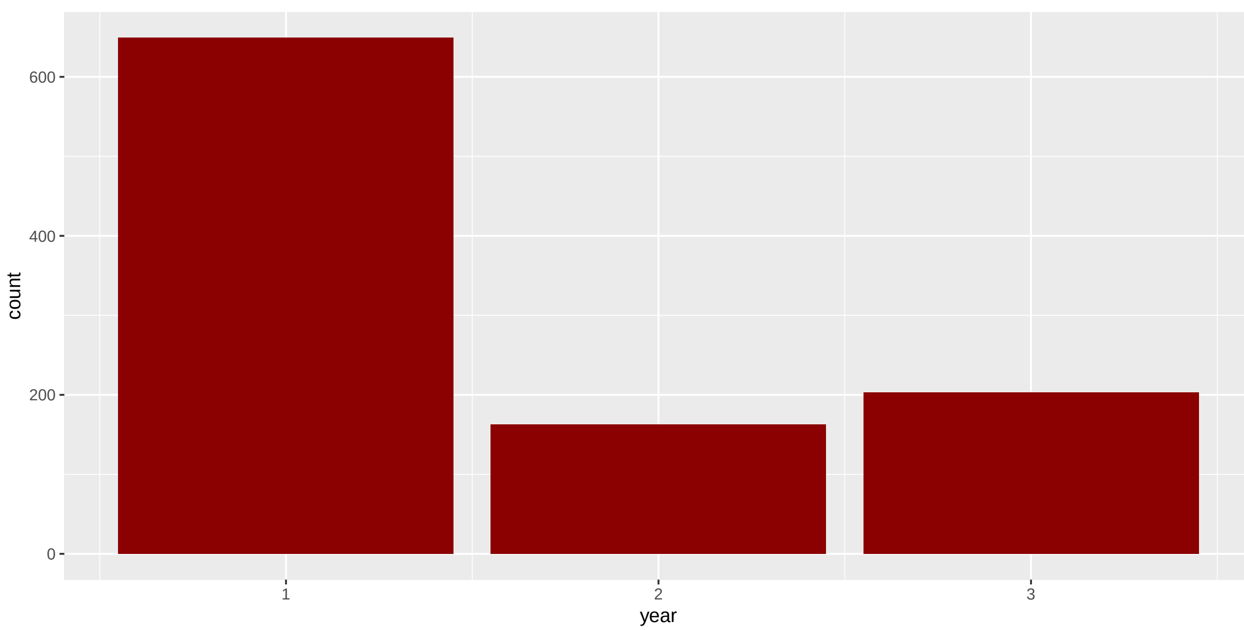
AAU Online - Frequency

```
freq(aau_desc_online$year, plain.ascii = TRUE, style = 'grid')
```

Frequencies
aau_desc_online$year
Type: Numeric

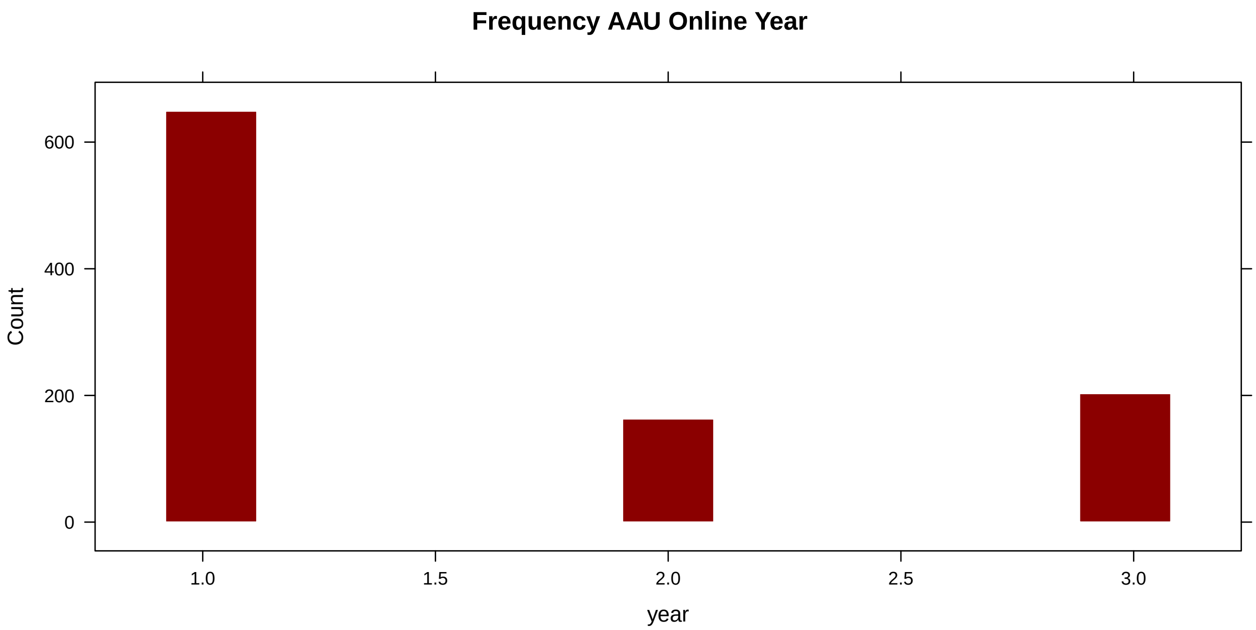
	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
1	649	63.94	63.94	63.94	63.94
2	163	16.06	80.00	16.06	80.00
3	203	20.00	100.00	20.00	100.00
<NA>	0			0.00	100.00
Total	1015	100.00	100.00	100.00	100.00

```
ggplot(aau_desc_online, aes(year)) + geom_bar(fill = "darkred")
```



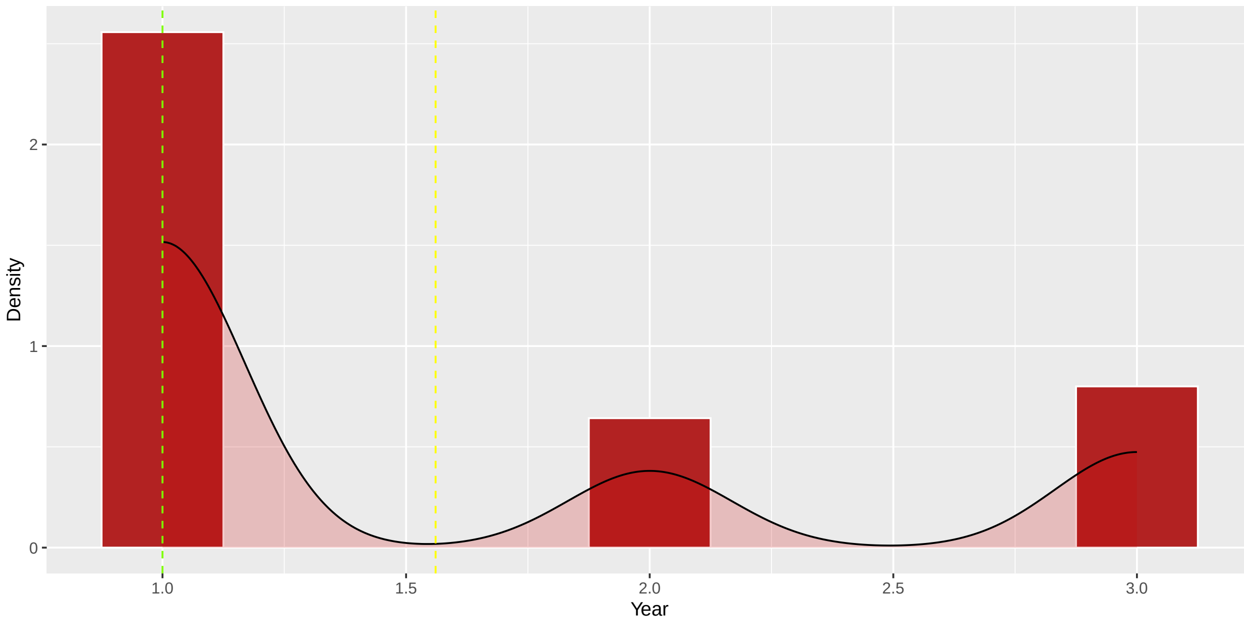
AAU Online - Histogram

```r
histogram(aau_desc_online$year, type = "count", main='Frequency AAU Online Year',
          xlab='year', col='darkred', border = "white")
```



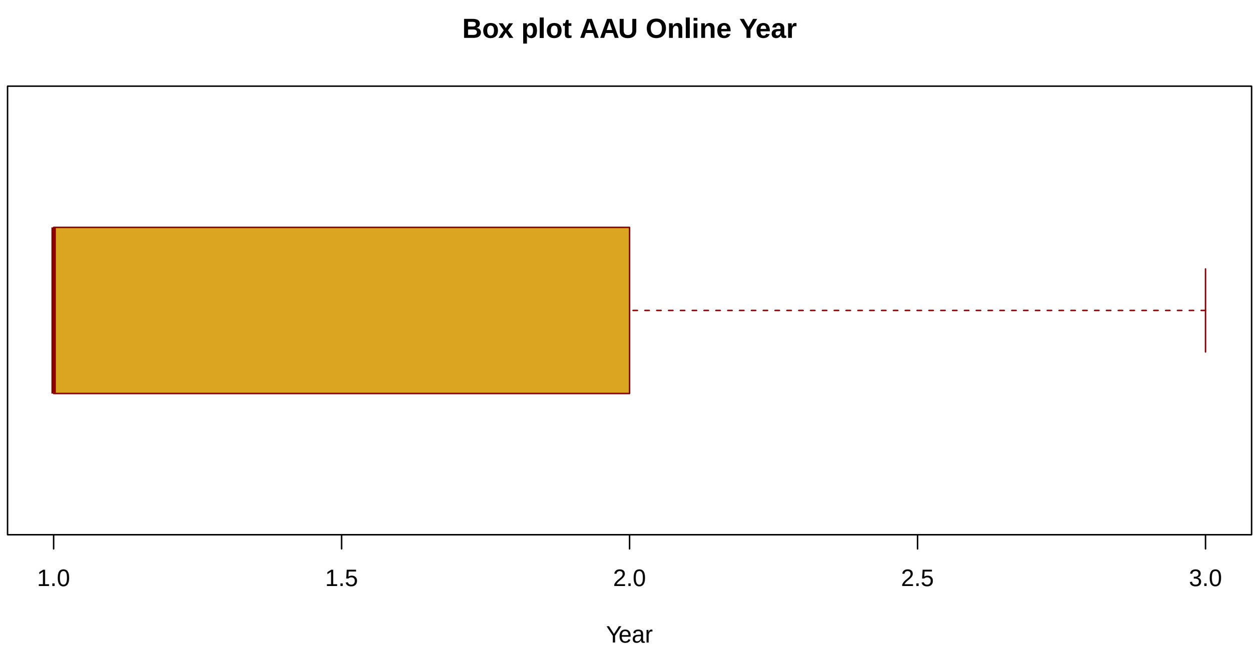
AAU Online - Histogram with density

```r
ggplot(aau_desc_online, aes(x=year)) +
 geom_histogram(aes(y=..density..), binwidth= .25, colour="white", fill="firebrick")+
 geom_density(alpha=.2, fill="red3") +
geom_vline(aes(xintercept=mean(year)), color="yellow", linetype="dashed") +
  geom_vline(aes(xintercept=median(year)), color="chartreuse", linetype="dashed") +
  labs(x="Year", y="Density")
```



AAU Online - Box plot

```
boxplot(aau_desc_online$year, main = "Box plot AAU Online Year", xlab = "Year",
col = "goldenrod", border = "darkred", horizontal = TRUE, notch = FALSE)
```



Degree Program

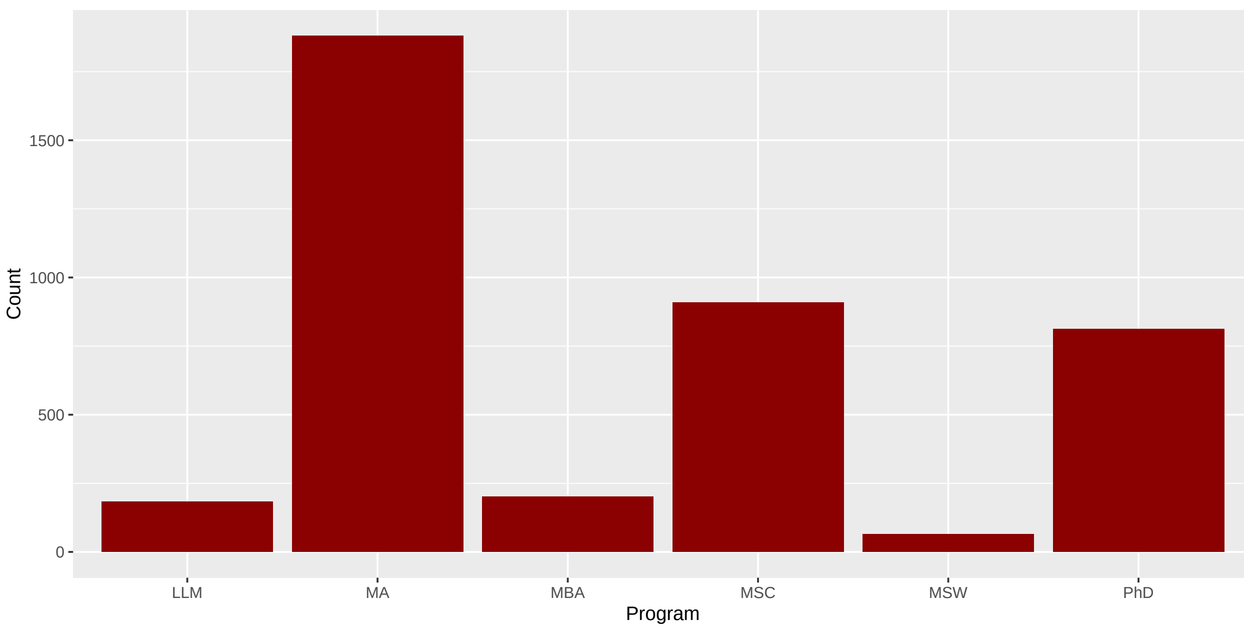
AAU Dataset - Frequency

```
freq(aau_desc_all$prog, plain.ascii = TRUE, style = 'grid')
```

Frequencies
aau_desc_all$prog
Type: Character

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
LLM	184	4.54	4.54	4.54	4.54
MA	1880	46.41	50.95	46.41	50.95
MBA	201	4.96	55.91	4.96	55.91
MSC	909	22.44	78.35	22.44	78.35
MSW	64	1.58	79.93	1.58	79.93
PhD	813	20.07	100.00	20.07	100.00
<NA>	0			0.00	100.00
Total	4051	100.00	100.00	100.00	100.00

```
ggplot(aau_desc_all, aes(prog)) + xlab("Program") + ylab("Count") +
  geom_bar(fill = "darkred")
```



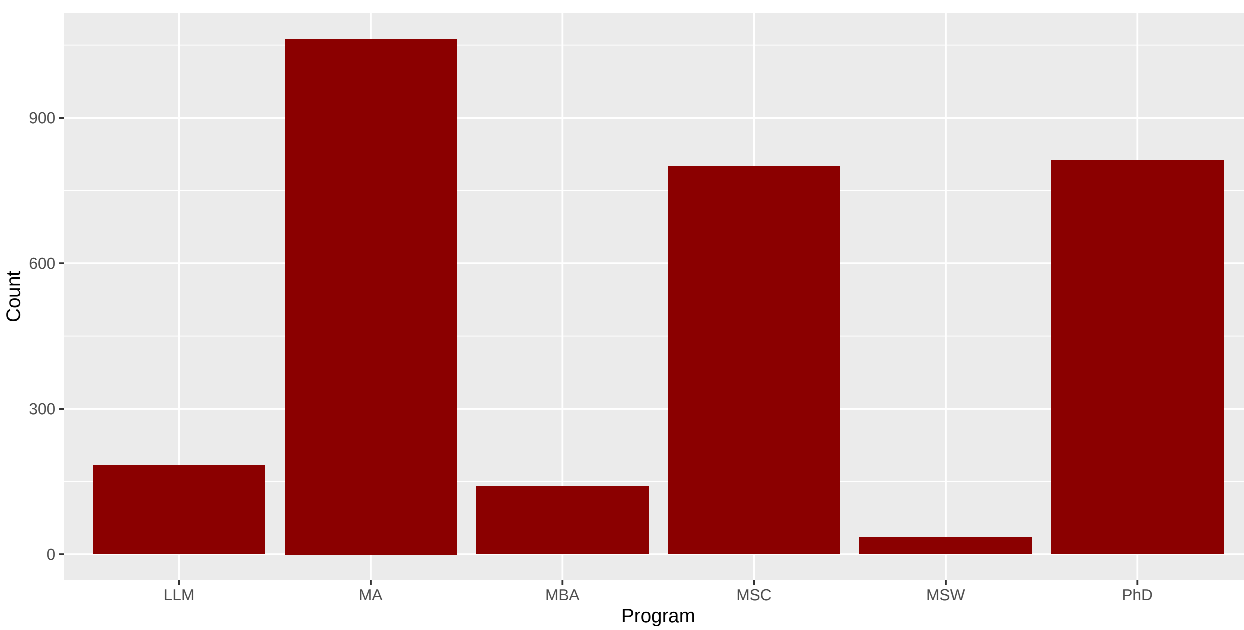
AAU Campus - Frequency

```
freq(aau_desc_campus$prog, plain.ascii = TRUE, style = 'grid')
```

Frequencies
aau_desc_campus$prog
Type: Character

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
LLM	184	6.06	6.06	6.06	6.06
MA	1063	35.01	41.07	35.01	41.07
MBA	141	4.64	45.72	4.64	45.72
MSC	800	26.35	72.07	26.35	72.07
MSW	35	1.15	73.22	1.15	73.22
PhD	813	26.78	100.00	26.78	100.00
<NA>	0			0.00	100.00
Total	3036	100.00	100.00	100.00	100.00

```
ggplot(aau_desc_campus, aes(prog)) + xlab("Program") + ylab("Count") +
  geom_bar(fill = "darkred")
```



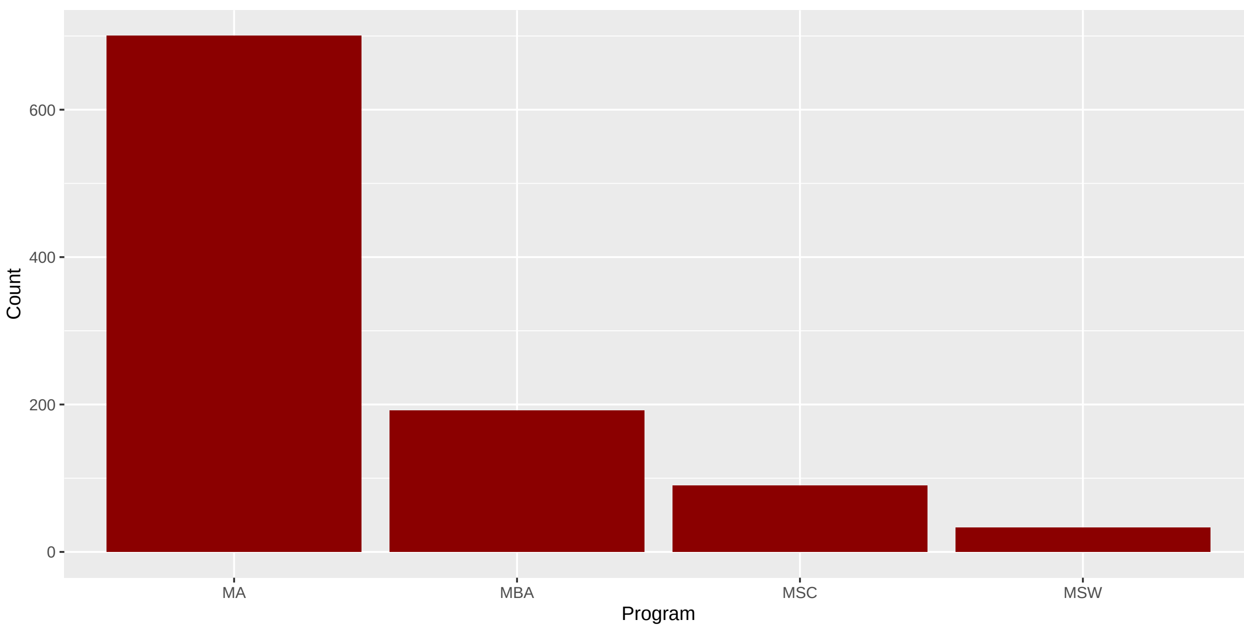
AAu Online - Frequency

```r
freq(aau_desc_online$prog, plain.ascii = TRUE, style = 'grid')
```

Frequencies
aau_desc_online$prog
Type: Character

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
MA	700	68.97	68.97	68.97	68.97
MBA	192	18.92	87.88	18.92	87.88
MSC	90	8.87	96.75	8.87	96.75
MSW	33	3.25	100.00	3.25	100.00
<NA>	0			0.00	100.00
Total	1015	100.00	100.00	100.00	100.00

```r
ggplot(aau_desc_online, aes(prog)) + xlab("Program") + ylab("Count") +
  geom_bar(fill = "darkred")
```



College/Unit

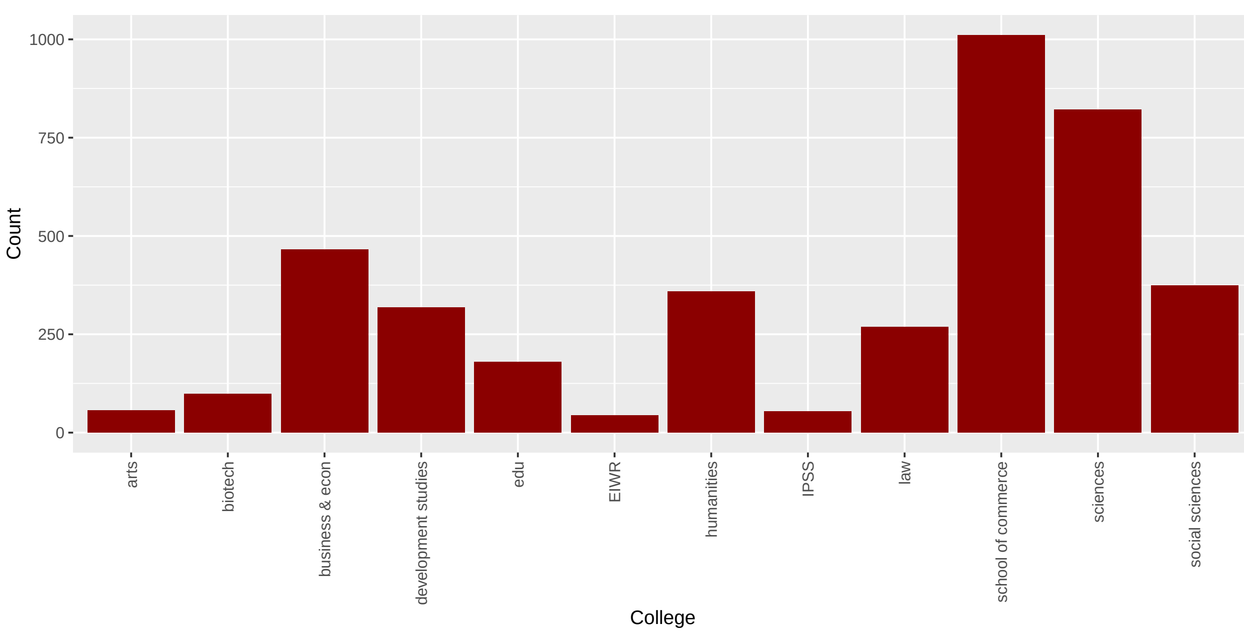
AAU Dataset - Frequency

```
freq(aau_desc_all$coll, plain.ascii = TRUE, style = 'grid')
```

Frequencies
aau_desc_all$coll
Type: Character

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
arts	57	1.41	1.41	1.41	1.41
biotech	99	2.44	3.85	2.44	3.85
business & econ	465	11.48	15.33	11.48	15.33
development studies	318	7.85	23.18	7.85	23.18
edu	180	4.44	27.62	4.44	27.62
EIWR	44	1.09	28.71	1.09	28.71
humanities	359	8.86	37.57	8.86	37.57
IPSS	54	1.33	38.90	1.33	38.90
law	269	6.64	45.54	6.64	45.54
school of commerce	1011	24.96	70.50	24.96	70.50
sciences	821	20.27	90.77	20.27	90.77
social sciences	374	9.23	100.00	9.23	100.00
<NA>	0			0.00	100.00
Total	4051	100.00	100.00	100.00	100.00

```
ggplot(aau_desc_all, aes(coll)) +
  xlab("College") + ylab("Count") + geom_bar(fill = "darkred") +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))
```



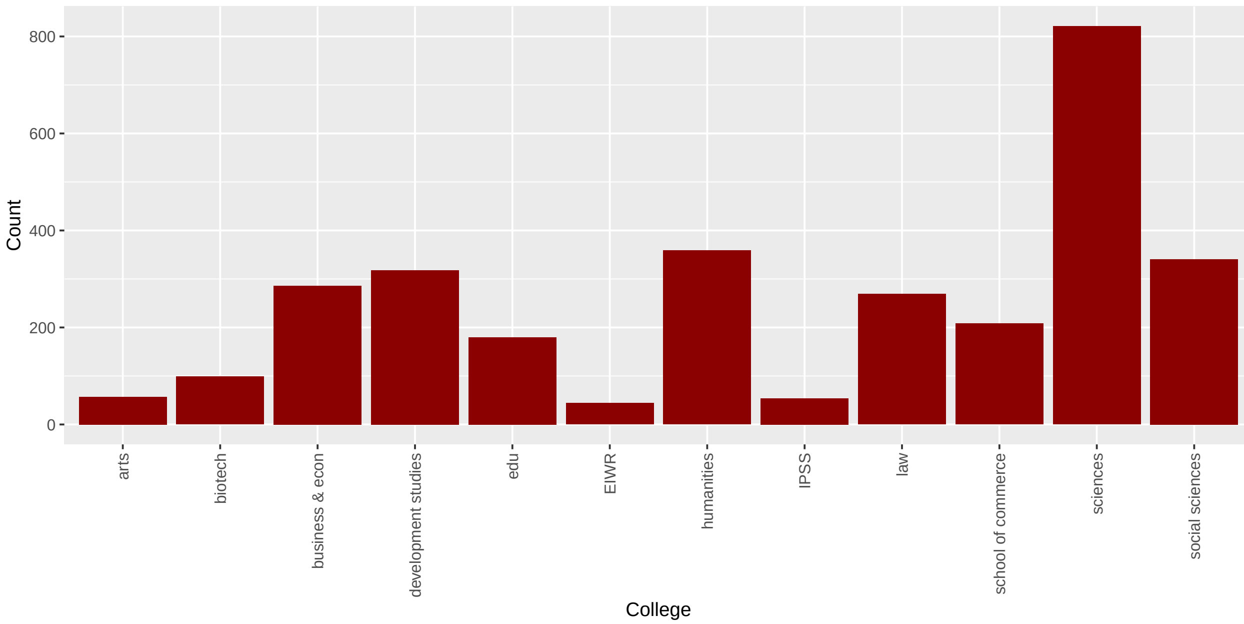
AAU Campus - Frequency

```
freq(aau_desc_campus$coll, plain.ascii = TRUE, style = 'grid')
```

Frequencies
aau_desc_campus$coll
Type: Character

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
arts	57	1.88	1.88	1.88	1.88
biotech	99	3.26	5.14	3.26	5.14
business & econ	286	9.42	14.56	9.42	14.56
development studies	318	10.47	25.03	10.47	25.03
edu	180	5.93	30.96	5.93	30.96
EIWR	44	1.45	32.41	1.45	32.41
humanities	359	11.82	44.24	11.82	44.24
IPSS	54	1.78	46.01	1.78	46.01
law	269	8.86	54.87	8.86	54.87
school of commerce	208	6.85	61.73	6.85	61.73
sciences	821	27.04	88.77	27.04	88.77
social sciences	341	11.23	100.00	11.23	100.00
<NA>	0			0.00	100.00
Total	3036	100.00	100.00	100.00	100.00

```
ggplot(aau_desc_campus, aes(coll)) + xlab("College") + ylab("Count") +
  geom_bar(fill = "darkred") +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))
```



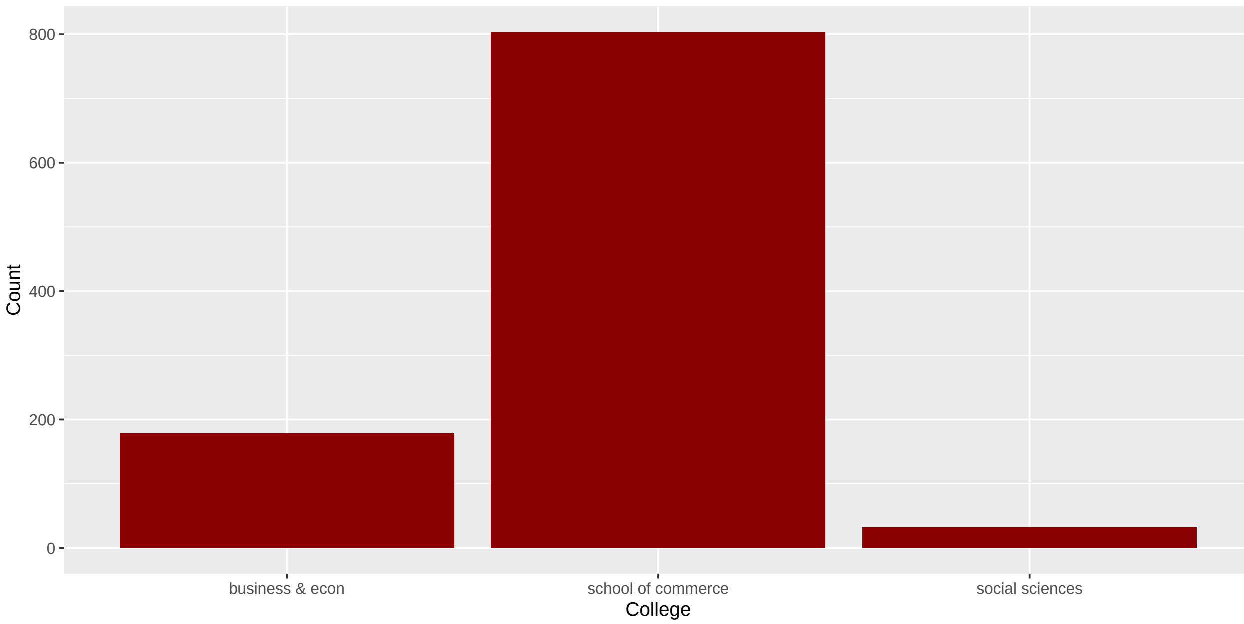
AAU Online - Frequency

```
freq(aau_desc_online$coll, plain.ascii = TRUE, style = 'grid')
```

Frequencies
aau_desc_online$coll
Type: Character

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
business & econ	179	17.64	17.64	17.64	17.64
school of commerce	803	79.11	96.75	79.11	96.75
social sciences	33	3.25	100.00	3.25	100.00
<NA>	0			0.00	100.00
Total	1015	100.00	100.00	100.00	100.00

```
ggplot(aau_desc_online, aes(coll)) + xlab("College") + ylab("Count") +
  geom_bar(fill = "darkred")
```


800
600
400
200
0
Count
business & econ
school of commerce
social sciences
College

Region

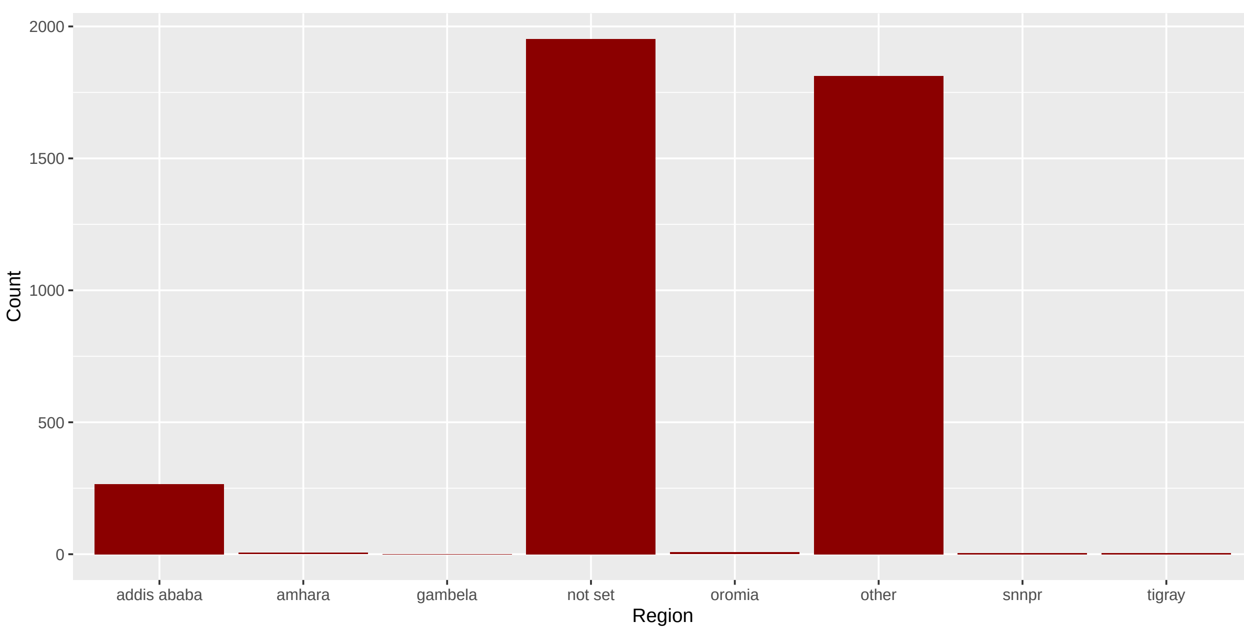
AAU Dataset - Frequency

```
freq(aau_desc_all$region, plain.ascii = TRUE, style = 'grid')
```

Frequencies
aau_desc_all$region
Type: Character

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
addis ababa	266	6.566	6.566	6.566	6.566
amhara	5	0.123	6.690	0.123	6.690
gambela	1	0.025	6.714	0.025	6.714
not set	1952	48.186	54.900	48.186	54.900
oromia	7	0.173	55.073	0.173	55.073
other	1812	44.730	99.803	44.730	99.803
snnpr	4	0.099	99.901	0.099	99.901
tigray	4	0.099	100.000	0.099	100.000
<NA>	0			0.000	100.000
Total	4051	100.000	100.000	100.000	100.000

```
ggplot(aau_desc_all, aes(region)) + xlab("Region") + ylab("Count") +
  geom_bar(fill = "darkred")
```



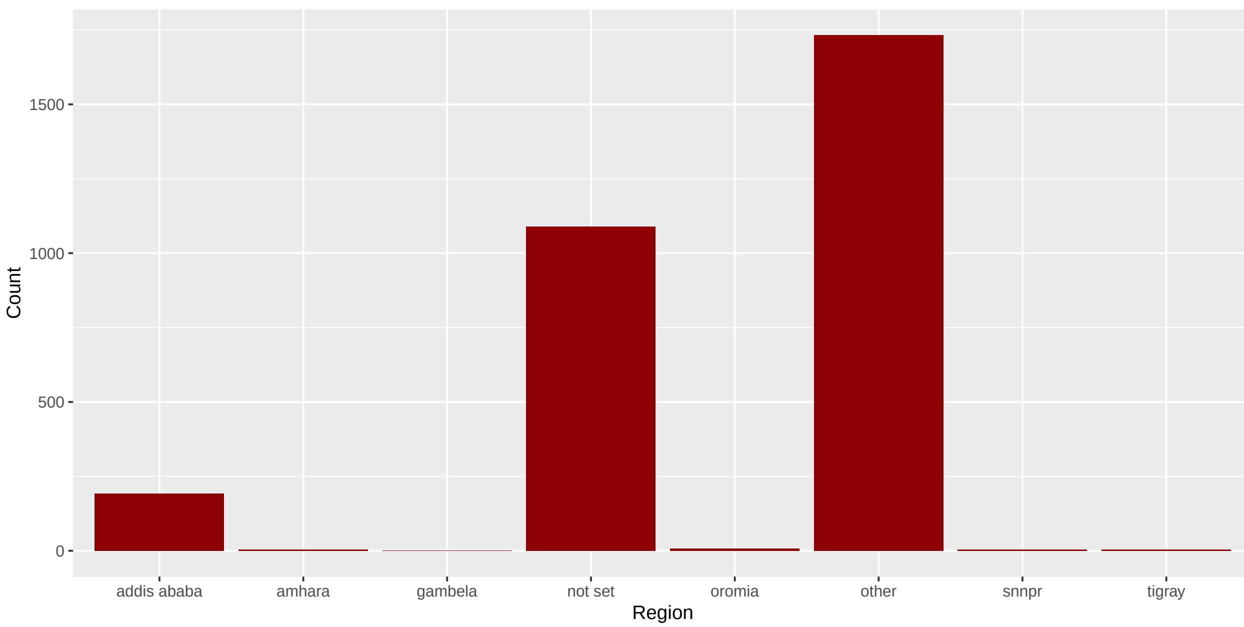
AAU Campus - Frequency

```
freq(aau_desc_campus$region, plain.ascii = TRUE, style = 'grid')
```

Frequencies
aau_desc_campus$region
Type: Character

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
addis ababa	193	6.357	6.357	6.357	6.357
amhara	5	0.165	6.522	0.165	6.522
gambela	1	0.033	6.555	0.033	6.555
not set	1090	35.903	42.457	35.903	42.457
oromia	7	0.231	42.688	0.231	42.688
other	1732	57.049	99.736	57.049	99.736
snnpr	4	0.132	99.868	0.132	99.868
tigray	4	0.132	100.000	0.132	100.000
<NA>	0			0.000	100.000
Total	3036	100.000	100.000	100.000	100.000

```
ggplot(aau_desc_campus, aes(region)) + xlab("Region") + ylab("Count") +
  geom_bar(fill = "darkred")
```



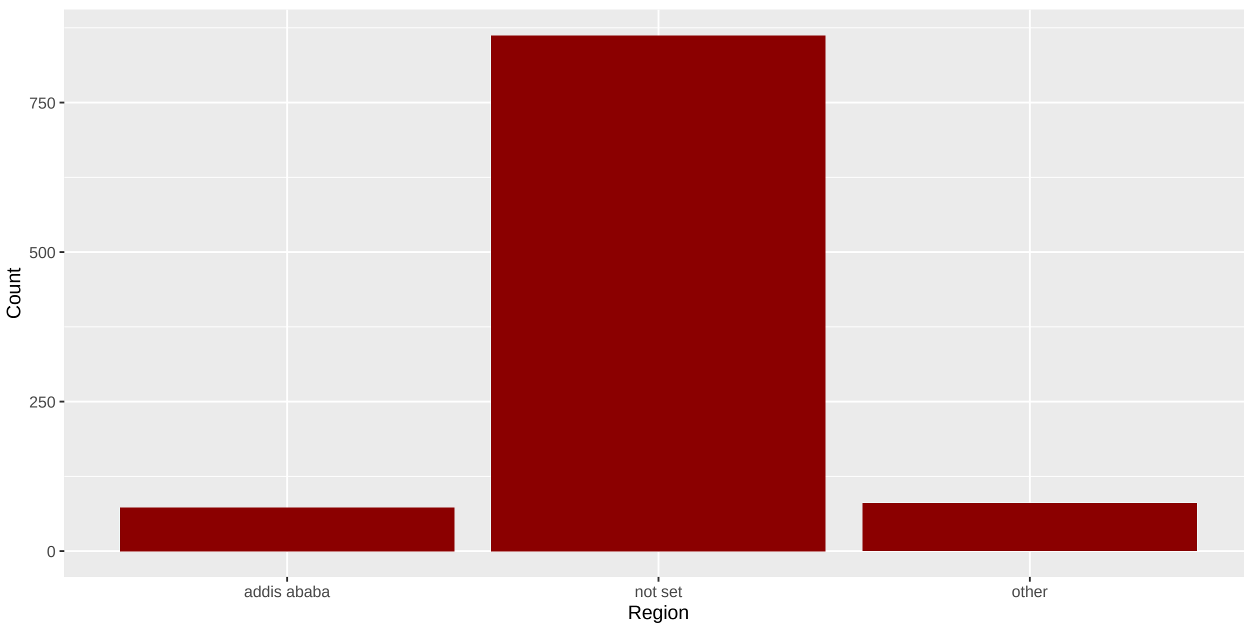
AAU Online - Frequency

```r
freq(aau_desc_online$region, plain.ascii = TRUE, style = 'grid')
```

Frequencies
aau_desc_online$region
Type: Character

	Freq	% Valid	% Valid Cum.	% Total	% Total Cum.
addis ababa	73	7.19	7.19	7.19	7.19
not set	862	84.93	92.12	84.93	92.12
other	80	7.88	100.00	7.88	100.00
<NA>	0			0.00	100.00
Total	1015	100.00	100.00	100.00	100.00

```r
ggplot(aau_desc_online, aes(region)) + xlab("Region") + ylab("Count") +
  geom_bar(fill = "darkred")
```



Addis Ababa University

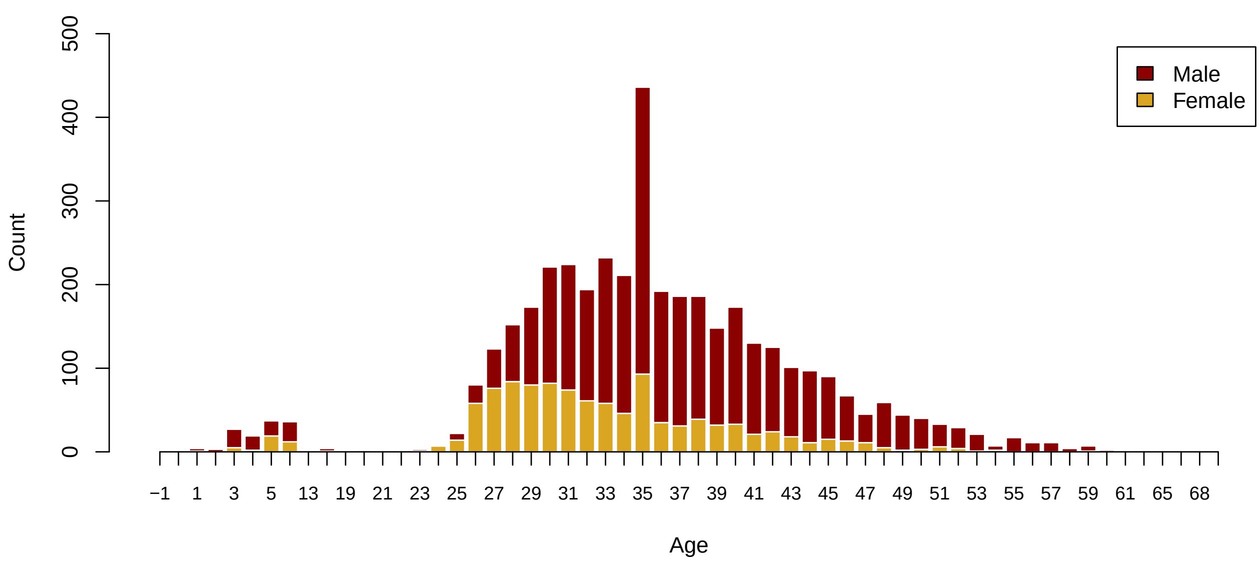
Gender-based Descriptive Statistics

Gender Analysis

Gender distribution by age

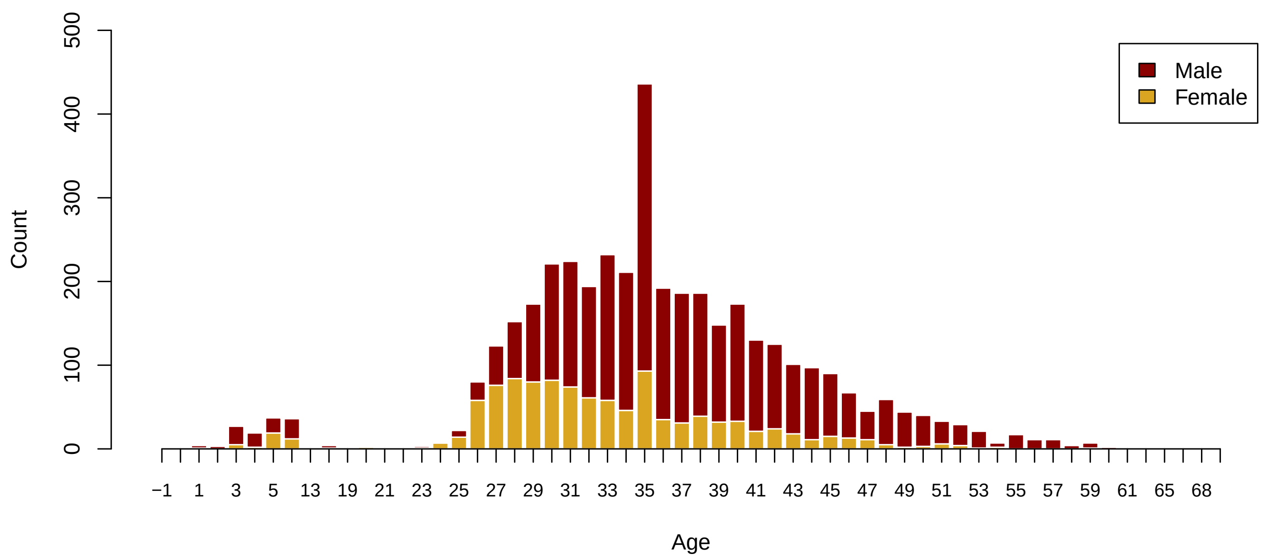
All Students

```
aau_gender_threeway <- xtabs(~gender + age, data=aau_desc_gender)
aau_gender_threeway_ftable <-ftable(aau_gender_threeway)

barplot(aau_gender_threeway,
        xlab = "Age", ylab= "Count",
        border = "white", col = c("goldenrod", "darkred"),
        cex.names = 0.8, ylim = c(0, 500),
        axis.lty = 1, legend = (c("Female", "Male"))
)
```

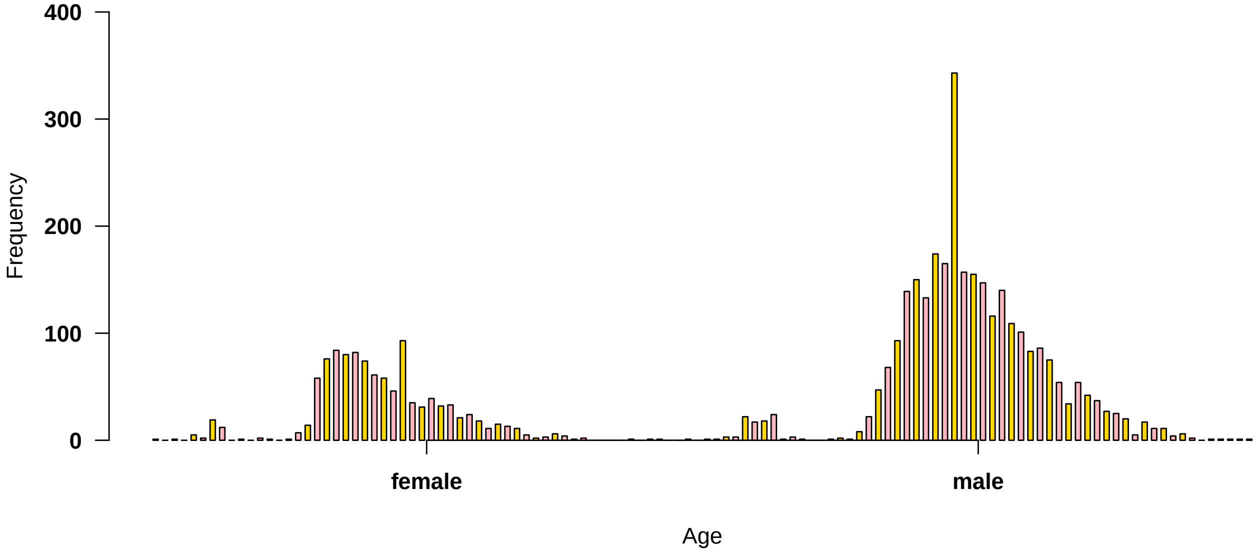


Online Students

```r
aau_gender_threeway <- xtabs(~gender + age, data=aau_desc_gender)
aau_gender_threeway_ftable <-ftable(aau_gender_threeway)

barplot(aau_gender_threeway,
        xlab = "Age", ylab= "Count",
        border = "white", col = c("goldenrod", "darkred"),
        cex.names = 0.8, ylim = c(0, 500),
        axis.lty = 1, legend = (c("Female", "Male"))
)
```

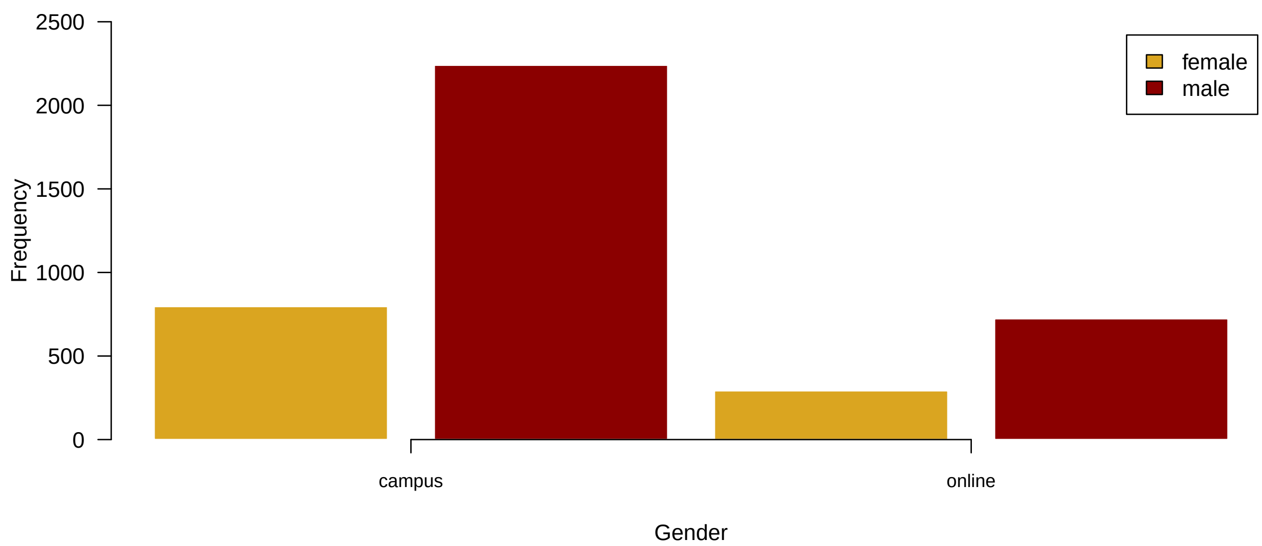



```r
barplot(table(aau_desc_gender$age, aau_desc_gender$gender), beside = TRUE,
        ylim = c(0, 400), axis.lty = 1,
         las = 1, col = c("gold", "lightpink"), font.axis = 2,
        cex.name = 1, space = c(0.8, 0.8),
        xlab = "Age", ylab = "Frequency",
         legend.text = FALSE)
```


400
300
200
100
0
Frequency
female
male
Age

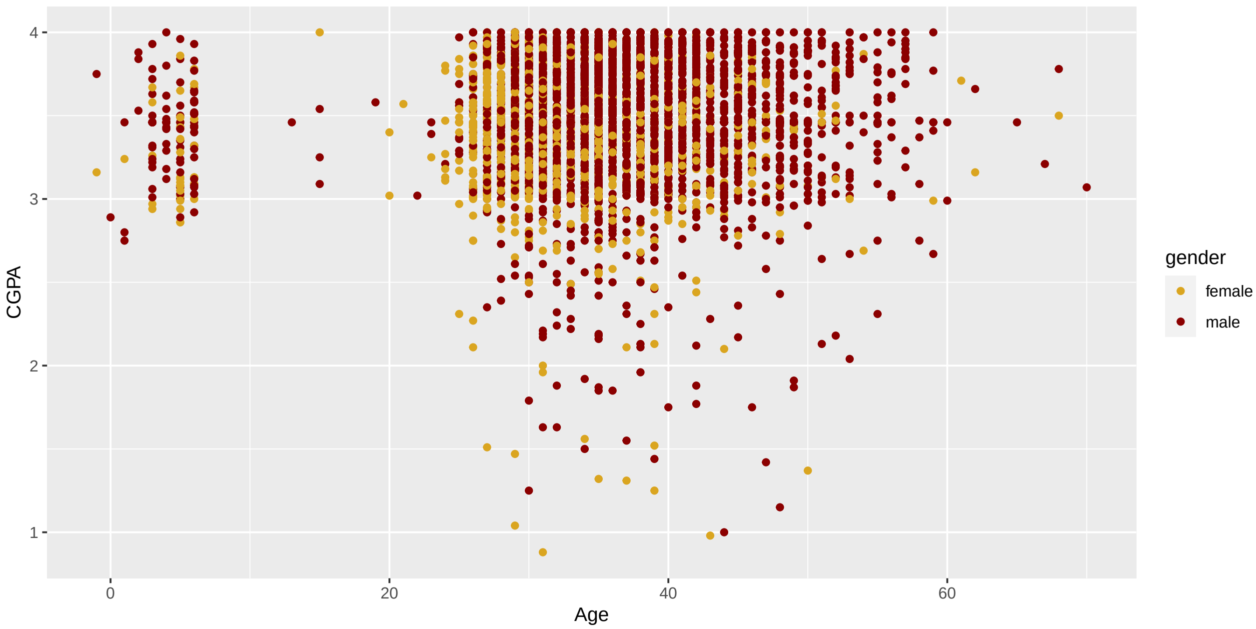
Gender distribution by modality

```
barplot(table(aau_desc_gender$gender, aau_desc_gender$modality), beside = TRUE,
        ylim = c(0, 2500), axis.lty = 1,
        las = 1, col = c("goldenrod", "darkred"), border= "white",
        cex.name = 0.8, space = c(0.2, 0.2),
        xlab = "Gender", ylab = "Frequency", legend.text = TRUE)
```



Gender distribution by age and CGPA

```
ggplot(aau_desc_gender, aes(x = age, y = cgpa, color = gender)) +
  geom_point() +
  labs(x = "Age", y = "CGPA") +
  scale_color_manual(values = c("goldenrod", "darkred"))
```

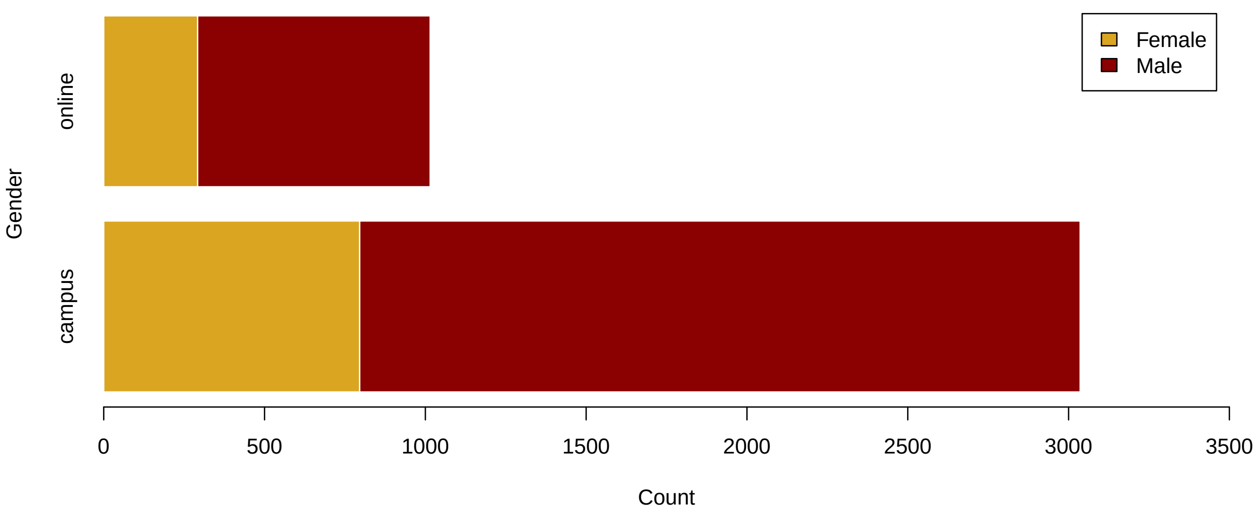



```
table(aau_desc_gender$gender, aau_desc_gender$modality)
```

```
     campus online
```

female 796 292 male 2240 723

```
aau_gender_threeway <- xtabs(~gender + modality, data=aau_desc_gender)
aau_gender_threeway_ftable <-ftable(aau_gender_threeway)

barplot(aau_gender_threeway,
        xlab = "Count",
        ylab= "Gender",
        horiz = TRUE,
        col = c("goldenrod", "darkred"),
        border = "white", xlim = c(0, 3500),
        legend = (c("Female", "Male"))
)
```



Gender distribution by age and CGPA

```
ggplot(aau_desc_gender, aes(x = age, y = cgpa, color = gender)) +
  geom_point() +
  labs(x = "Age", y = "CGPA") +
  scale_color_manual(values = c("goldenrod", "darkred"))
```

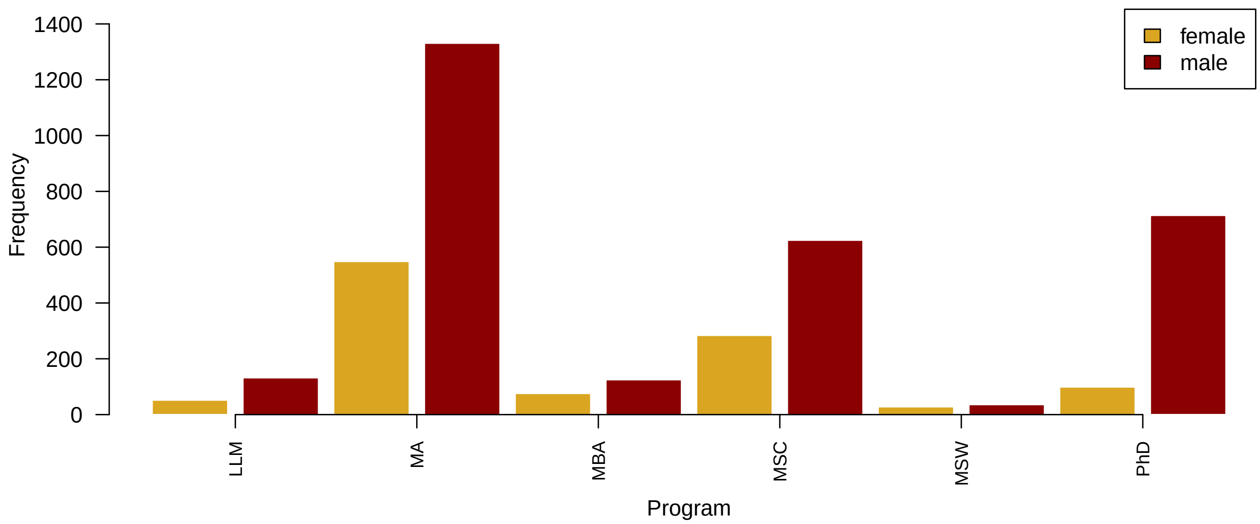
Gender distribution by degree program

```
table(aau_desc_gender$gender, aau_desc_gender$prog)
```

```
      LLM   MA  MBA  MSC  MSW  PhD
```

female 52 549 76 284 28 99 male 132 1331 125 625 36 714

```
barplot(table(aau_desc_gender$gender, aau_desc_gender$prog), beside = TRUE,
        ylim = c(0, 1500), axis.lty = 1,
        las = 1, col = c("goldenrod", "darkred"), border= "white",
        cex.name = 0.8, space = c(0.2, 0.2),
        xlab = "Program", ylab = "Frequency", las = 2, legend.text = TRUE)
```

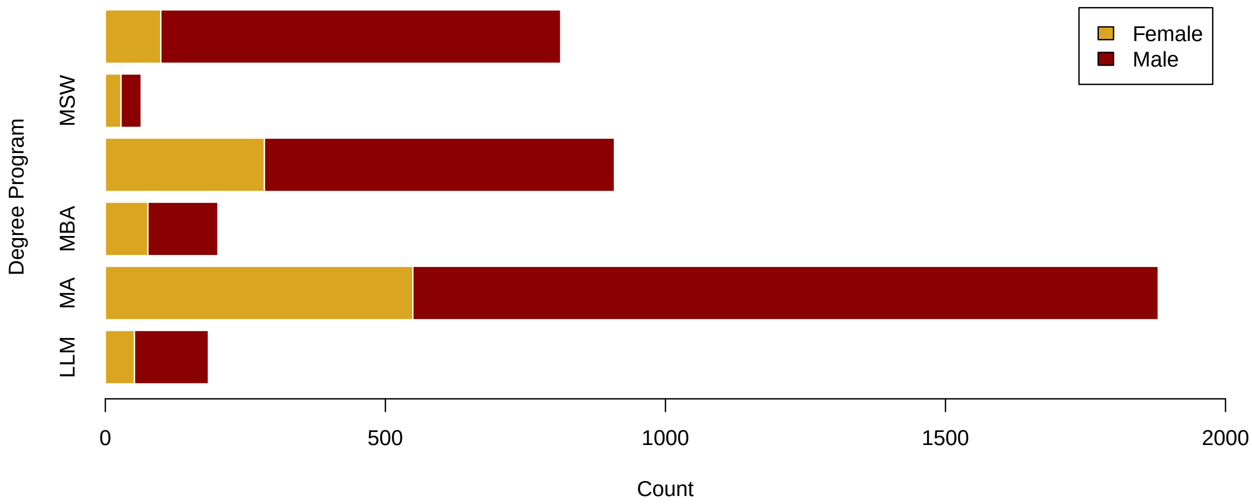


```
table(aau_desc_gender$gender, aau_desc_gender$prog)
```

```
      LLM   MA  MBA  MSC  MSW  PhD
```

female 52 549 76 284 28 99 male 132 1331 125 625 36 714

```
aau_gender_threeway <- xtabs(~gender + prog, data=aau_desc_gender)
aau_gender_threeway_ftable <-ftable(aau_gender_threeway)

barplot(aau_gender_threeway,
        xlab = "Count",
        ylab= "Degree Program",
        horiz = TRUE,
        col = c("goldenrod", "darkred"),
        border = "white", xlim = c(0, 2000),
        legend = (c("Female", "Male"))
)
```


Female
Male
Degree Program
MSW
MBA
MA
LLM
0
500
1000
1500
2000
Count

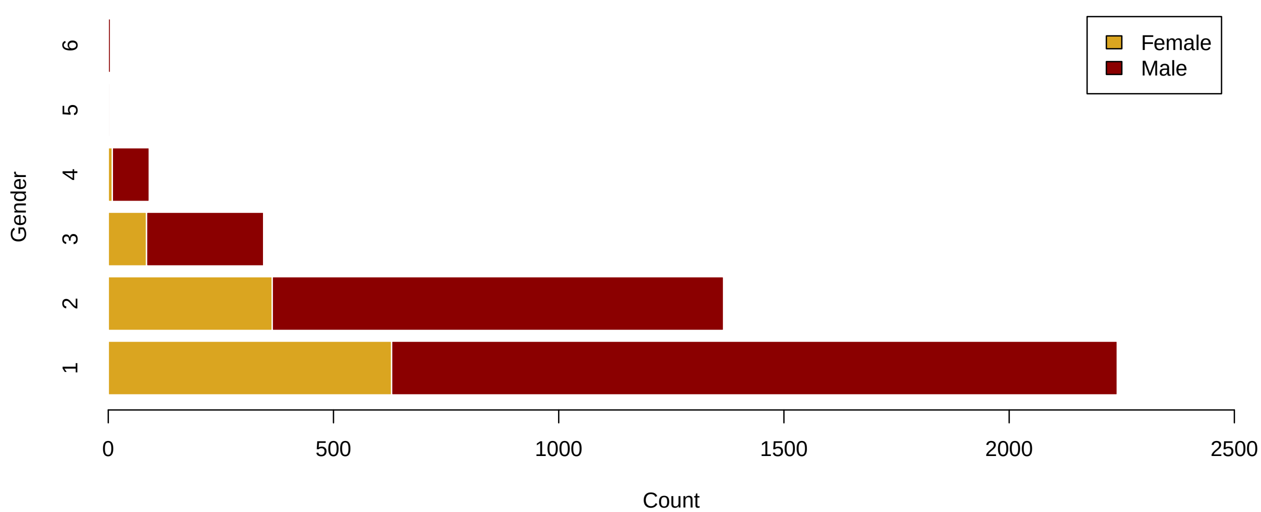
Gender distribution by year (level)

```
table(aau_desc_gender$gender, aau_desc_gender$year)
```

```
        1    2    3    4    5    6
```

female 629 364 85 9 1 0 male 1611 1002 260 82 3 5

```
aau_gender_threeway <- xtabs(~gender + year, data=aau_desc_gender)
aau_gender_threeway_ftable <-ftable(aau_gender_threeway)

barplot(aau_gender_threeway,
        xlab = "Count",
        ylab= "Gender",
        horiz = TRUE,
        col = c("goldenrod", "darkred"),
        border = "white", xlim = c(0, 2500),
        legend = (c("Female", "Male"))
)
```



Gender distribution by college

```
table(aau_desc_gender$gender, aau_desc_gender$coll)
```

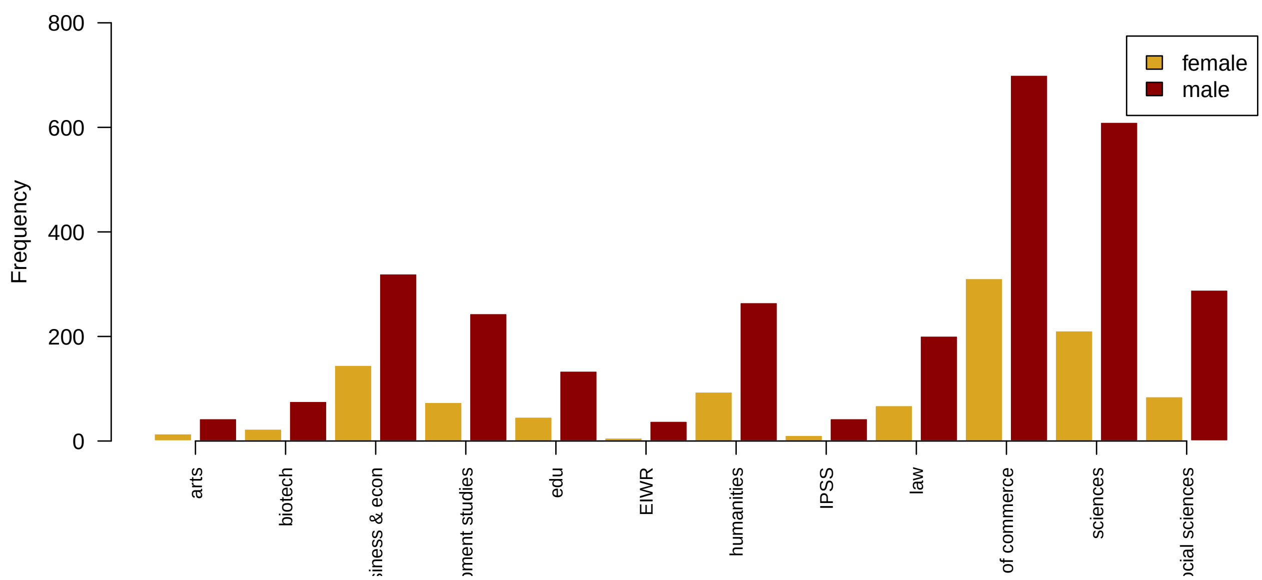
```
     arts biotech business & econ development studies edu EIWR humanities
```

female 14 23 145 74 46 6 94 male 43 76 320 244 134 38 265

```
     IPSS law school of commerce sciences social sciences
```

female 11 68 311 211 85 male 43 201 700 610 289

```
barplot(table(aau_desc_gender$gender, aau_desc_gender$coll), beside = TRUE,
        ylim = c(0, 800), axis.lty = 1,
        las = 1, col = c("goldenrod", "darkred"), border= "white",
        cex.name = 0.8, space = c(0.2, 0.2),
        xlab = "", ylab = "Frequency", las = 2, legend.text = TRUE)
```



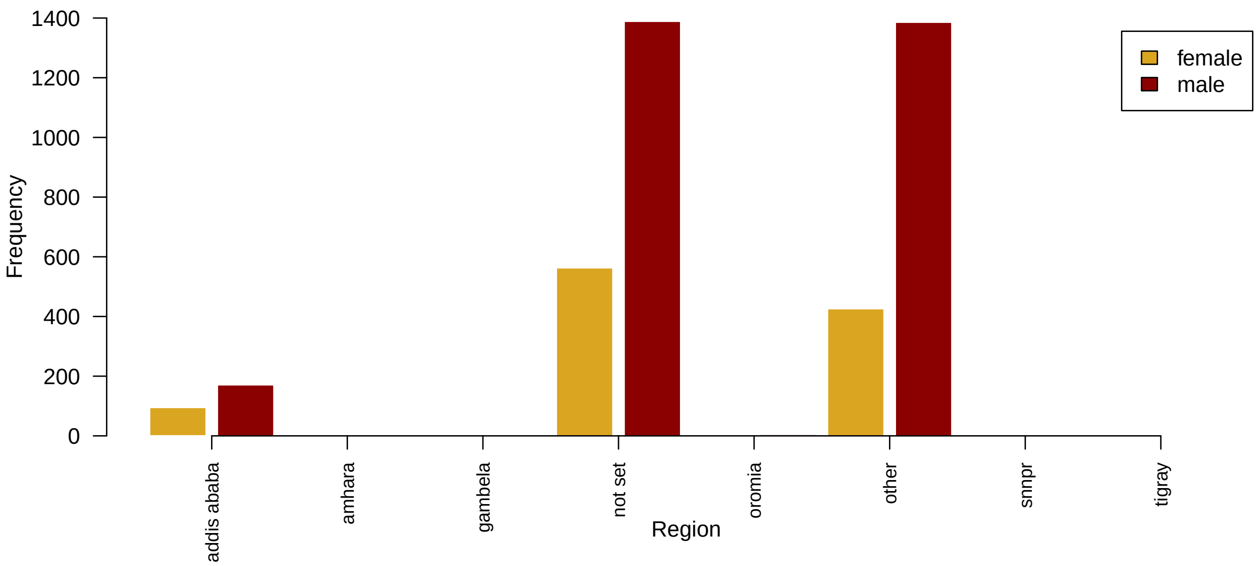
Gender distribution by region

```
table(aau_desc_gender$gender, aau_desc_gender$region)
```

```
     addis ababa amhara gambela not set oromia other snnpr tigray
```

female 95 1 0 563 2 426 0 1 male 171 4 1 1389 5 1386 4 3

```
barplot(table(aau_desc_gender$gender, aau_desc_gender$region), beside = TRUE,
        ylim = c(0, 1400), axis.lty = 1,
        las = 1, col = c("goldenrod", "darkred"), border= "white",
        cex.name = 0.8, space = c(0.2, 0.2),
        xlab = "Region", ylab = "Frequency", las = 2, legend.text = TRUE)
```



Addis Ababa University

Matching

Research Question

Is online instruction as effective as face-to-face instruction measured by Cumulative Grade Point Average (CGPA)?

MatchIt

Pre-matching balance assessment.

```
#Logistic Regression with method set to NULL to assess balance before matching
aaum.out0 <- matchit(treat ~ cgpa + age + gender + region + prog + semester,
                     data = aau_dv,
                 method = NULL, distance = "glm")
summary(aaum.out0)
```

```
##
## Call:
## matchit(formula = treat ~ cgpa + age + gender + region + prog +
##     semester, data = aau_dv, method = NULL, distance = "glm")
##
## Summary of Balance for All Data:
##                    Means Treated Means Control Std. Mean Diff. Var. Ratio
## distance                  0.6732        0.1093          2.1020     2.2624
## cgpa                      3.2568        3.5313         -0.6691     1.5267
## age                      36.6246       34.6644          0.1846     1.7635
## gender                    0.7123        0.7378         -0.0563          .
## regionaddis ababa         0.0719        0.0636          0.0323          .
## regionamhara              0.0000        0.0016         -0.0469          .
## regiongambela             0.0000        0.0003         -0.0210          .
## regionnot set             0.8493        0.3590          1.3702          .
## regionoromia              0.0000        0.0023         -0.0555          .
## regionother               0.0788        0.5705         -1.8247          .
## regionsnnpr               0.0000        0.0013         -0.0420          .
## regiontigray              0.0000        0.0013         -0.0420          .
## progLLM                   0.0000        0.0606         -0.2934          .
## progMA                    0.7911        0.3547          1.0735          .
## progMBA                   0.0877        0.0369          0.1796          .
## progMSC                   0.0887        0.2698         -0.6371          .
## progMSW                   0.0325        0.0102          0.1257          .
## progPhD                   0.0000        0.2678         -0.6986          .
```

```
## semester                 1.4443        1.0366           0.8202     7.0140
##                    eCDF Mean eCDF Max
## distance              0.4554   0.7740
## cgpa                  0.1304   0.3261
## age                   0.0607   0.2013
## gender                0.0255   0.0255
## regionaddis ababa     0.0084   0.0084
## regionamhara          0.0016   0.0016
## regiongambela         0.0003   0.0003
## regionnot set         0.4902   0.4902
## regionoromia          0.0023   0.0023
## regionother           0.4917   0.4917
## regionsnnpr           0.0013   0.0013
## regiontigray          0.0013   0.0013
## progLLM               0.0606   0.0606
## progMA                0.4364   0.4364
## progMBA               0.0508   0.0508
## progMSC               0.1811   0.1811
## progMSW               0.0223   0.0223
## progPhD               0.2678   0.2678
## semester              0.2039   0.4078
##
## Sample Sizes:
##           Control Treated
## All          3036    1015
## Matched      3036    1015
## Unmatched       0       0
## Discarded       0       0
```

Matching

```r
#Matching set to glm for generalized linear model for logistic regression

aaum.out1 <- matchit(treat ~ cgpa + age + gender +  region + prog + semester,
                     data = aau_dv,
                 method = "subclass", distance = "glm", link = "logit")
summary(aaum.out1)
```

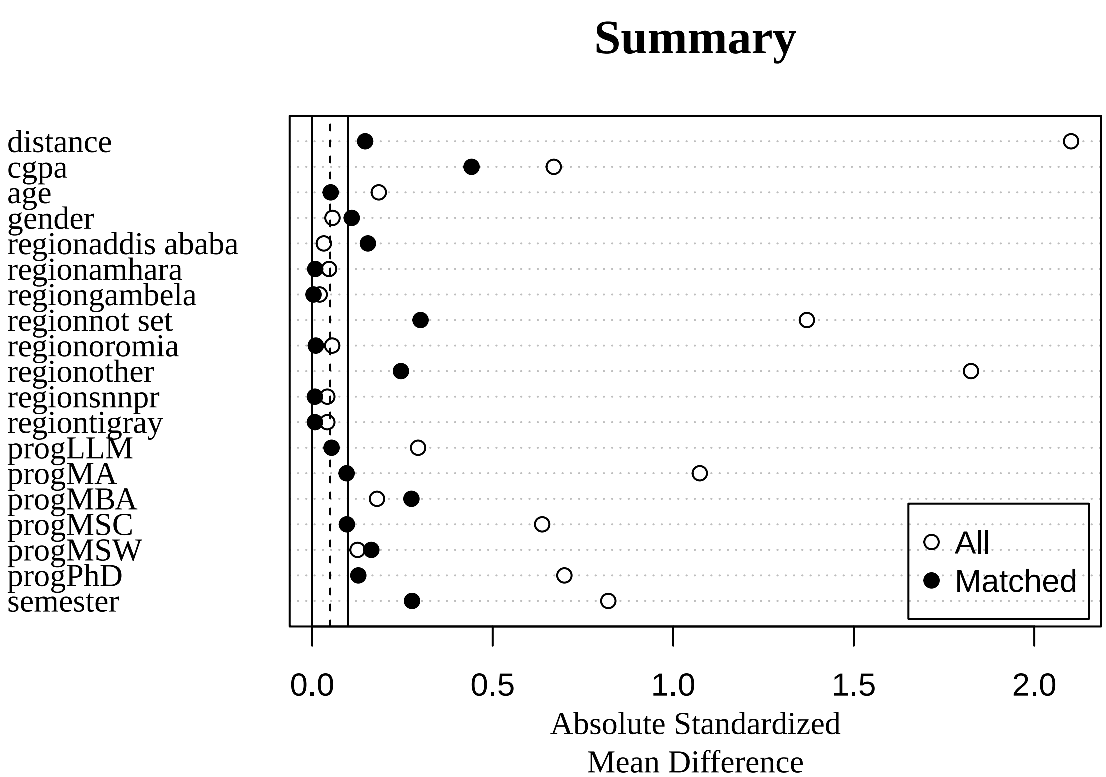
```
##
## Call:
## matchit(formula = treat ~ cgpa + age + gender + region + prog +
##     semester, data = aau_dv, method = "subclass", distance = "glm",
##     link = "logit")
##
## Summary of Balance for All Data:
##                     Means Treated Means Control Std. Mean Diff. Var. Ratio
## distance                   0.6732        0.1093          2.1020     2.2624
## cgpa                       3.2568        3.5313         -0.6691     1.5267
## age                       36.6246       34.6644          0.1846     1.7635
## gender                     0.7123        0.7378         -0.0563          .
## regionaddis ababa          0.0719        0.0636          0.0323          .
## regionamhara               0.0000        0.0016         -0.0469          .
## regiongambela              0.0000        0.0003         -0.0210          .
## regionnot set              0.8493        0.3590          1.3702          .
## regionoromia               0.0000        0.0023         -0.0555          .
## regionother                0.0788        0.5705         -1.8247          .
## regionsnnpr                0.0000        0.0013         -0.0420          .
## regiontigray               0.0000        0.0013         -0.0420          .
## progLLM                    0.0000        0.0606         -0.2934          .
## progMA                     0.7911        0.3547          1.0735          .
## progMBA                    0.0877        0.0369          0.1796          .
## progMSC                    0.0887        0.2698         -0.6371          .
## progMSW                    0.0325        0.0102          0.1257          .
## progPhD                    0.0000        0.2678         -0.6986          .
## semester                   1.4443        1.0366          0.8202     7.0140
##                     eCDF Mean eCDF Max
## distance               0.4554   0.7740
## cgpa                   0.1304   0.3261
## age                    0.0607   0.2013
## gender                 0.0255   0.0255
## regionaddis ababa      0.0084   0.0084
## regionamhara           0.0016   0.0016
## regiongambela          0.0003   0.0003
## regionnot set          0.4902   0.4902
## regionoromia           0.0023   0.0023
## regionother            0.4917   0.4917
## regionsnnpr            0.0013   0.0013
## regiontigray           0.0013   0.0013
## progLLM                0.0606   0.0606
## progMA                 0.4364   0.4364
## progMBA                0.0508   0.0508
## progMSC                0.1811   0.1811
```

```
## progMSW              0.0223   0.0223
## progPhD              0.2678   0.2678
## semester             0.2039   0.4078
##
## Summary of Balance Across Subclasses
##                   Means Treated Means Control Std. Mean Diff. Var. Ratio
## distance                 0.6732        0.6338          0.1468     0.7302
## cgpa                     3.2568        3.0757          0.4415     0.4157
## age                     36.6246       37.1697         -0.0513     1.8471
## gender                   0.7123        0.7619         -0.1096          .
## regionaddis ababa        0.0719        0.1118         -0.1544          .
## regionamhara             0.0000        0.0003         -0.0086          .
## regiongambela            0.0000        0.0001         -0.0038          .
## regionnot set            0.8493        0.7419          0.3002          .
## regionoromia             0.0000        0.0004         -0.0102          .
## regionother              0.0788        0.1451         -0.2459          .
## regionsnnpr              0.0000        0.0002         -0.0077          .
## regiontigray             0.0000        0.0002         -0.0077          .
## progLLM                  0.0000        0.0111         -0.0537          .
## progMA                   0.7911        0.7524          0.0954          .
## progMBA                  0.0877        0.0099          0.2749          .
## progMSC                  0.0887        0.1160         -0.0962          .
## progMSW                  0.0325        0.0616         -0.1640          .
## progPhD                  0.0000        0.0490         -0.1279          .
## semester                 1.4443        1.3068          0.2766     1.1524
##                   eCDF Mean eCDF Max
## distance             0.0445   0.0972
## cgpa                 0.0671   0.1481
## age                  0.0329   0.1245
## gender               0.0496   0.0496
## regionaddis ababa    0.0399   0.0399
## regionamhara         0.0003   0.0003
## regiongambela        0.0001   0.0001
## regionnot set        0.1074   0.1074
## regionoromia         0.0004   0.0004
## regionother          0.0663   0.0663
## regionsnnpr          0.0002   0.0002
## regiontigray         0.0002   0.0002
## progLLM              0.0111   0.0111
## progMA               0.0388   0.0388
## progMBA              0.0778   0.0778
## progMSC              0.0274   0.0274
## progMSW              0.0291   0.0291
## progPhD              0.0490   0.0490
## semester             0.0688   0.1375
##
## Sample Sizes:
##               Control Treated
## All           3036.      1015
## Matched (ESS)  120.78    1015
## Matched       3036.      1015
## Unmatched        0.         0
## Discarded        0.         0
```

```
aaum.data <- match.data(aaum.out1)
```

Summary of matching

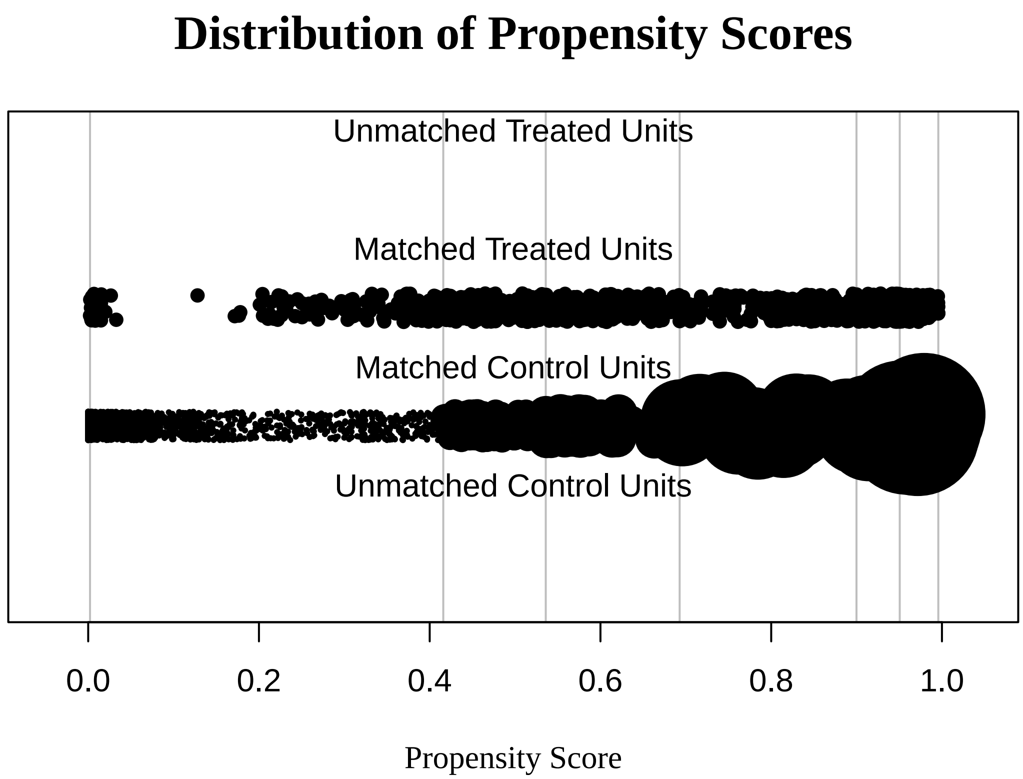
```
#Summary of matching
plot(summary(aaum.out1), main = "Summary", sub = "",
     family = "Times",
     cex.main = 1.5,
     cex.sub = 1,
     cex.lab = 1,
     cex.axis = 1,
     pch  = 16,
     col.main = "black",      # Title color
     col.sub = "black",        # Subtitle color
     col.lab = "black",     # X and Y-axis labels color
     col.axis = "black")    # Tick labels color
```



Checking balance

Distribution of propensity scores

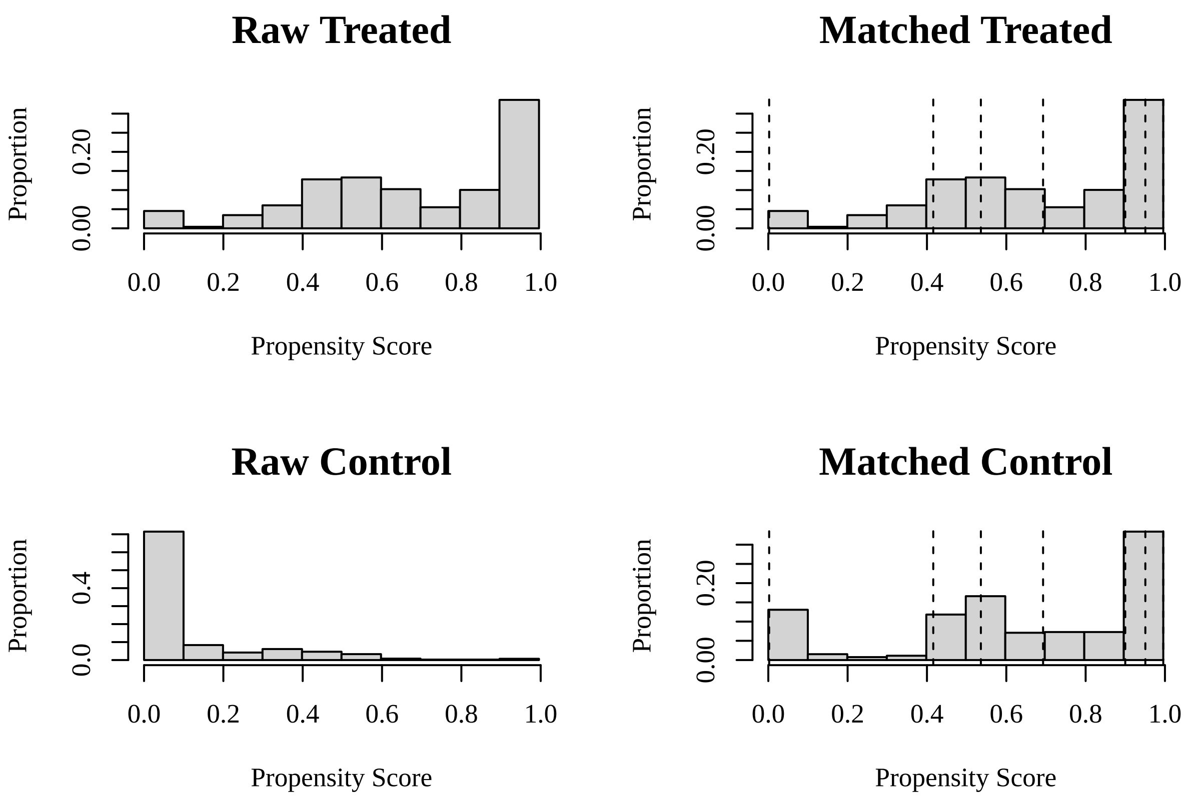
```
plot(aaum.out1, type = "jitter", interactive = FALSE,
     family = "Times",
     cex.main = 1.5,
     cex.sub = 1,
     cex.lab = 1,
     cex.axis = 1,
     pch  = 16,
     col.main = "black",      # Title color
     col.sub = "black",        # Subtitle color
     col.lab = "black",     # X and Y-axis labels color
     col.axis = "black")    # Tick labels color
```



Raw and treated histogram

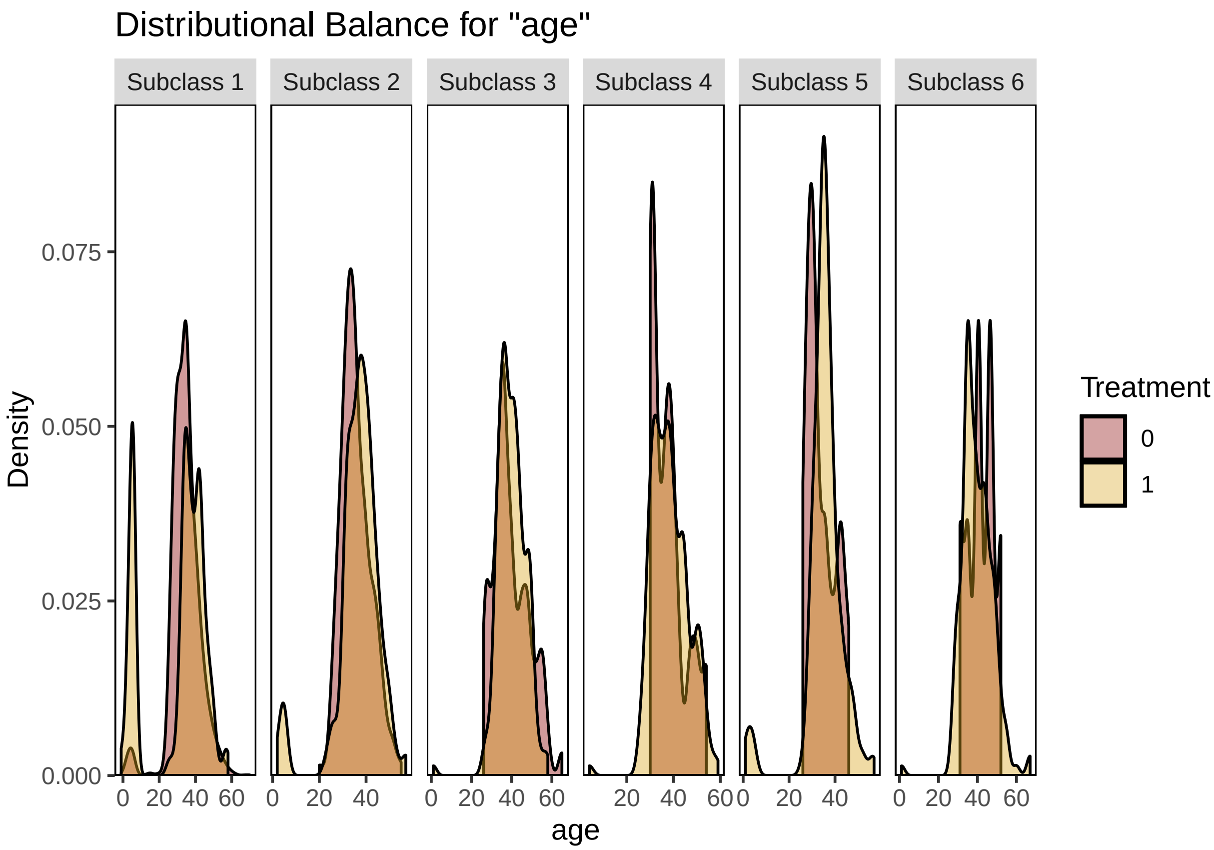
```
plot(aaum.out1, type = "histogram", interactive = TRUE,
     which.xs = ~ cgpa + age + gender + year,
    family = "Times",
     cex.main = 1.5,
     cex.sub = 1,
     cex.lab = 1,
     cex.axis = 1,
```

```
    col.main = "black",
    col.lab = "black",
    col.axis = "black")
```

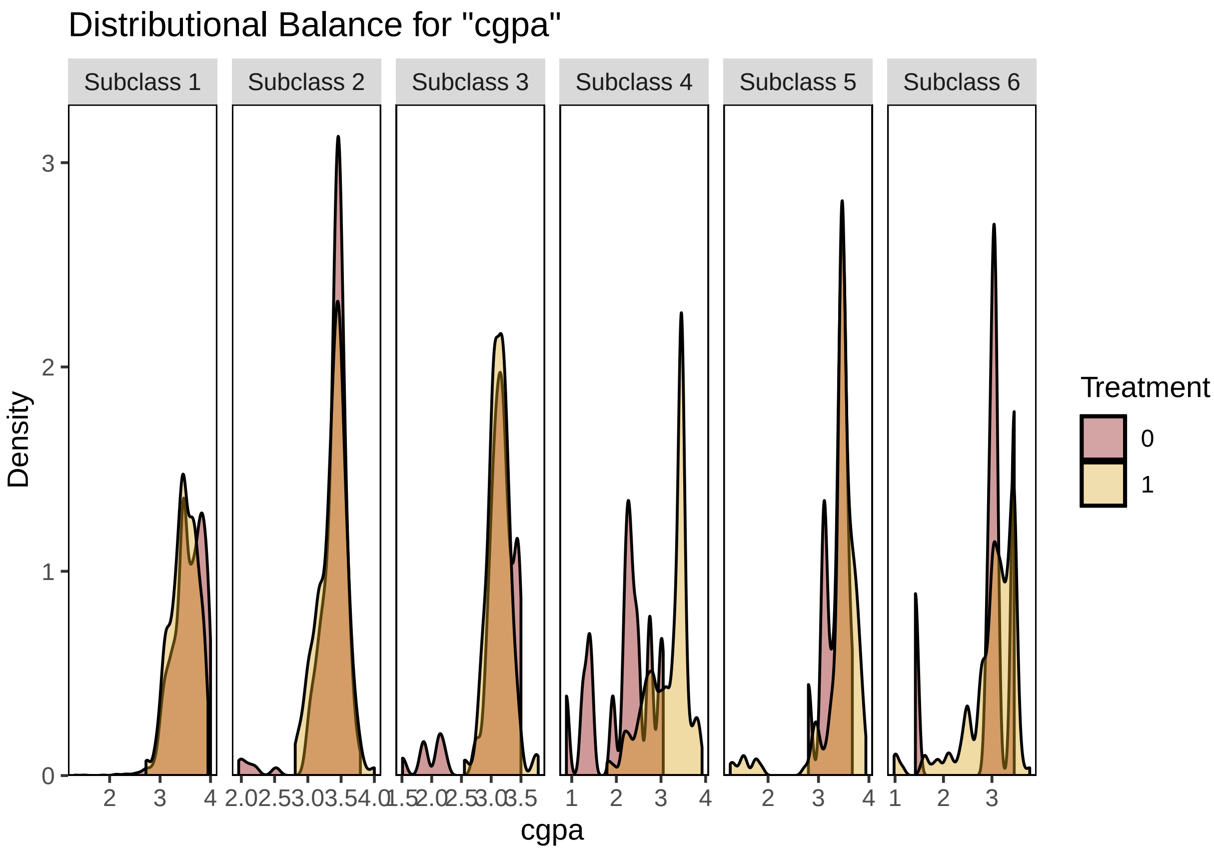


Distributional balance - covariate balance

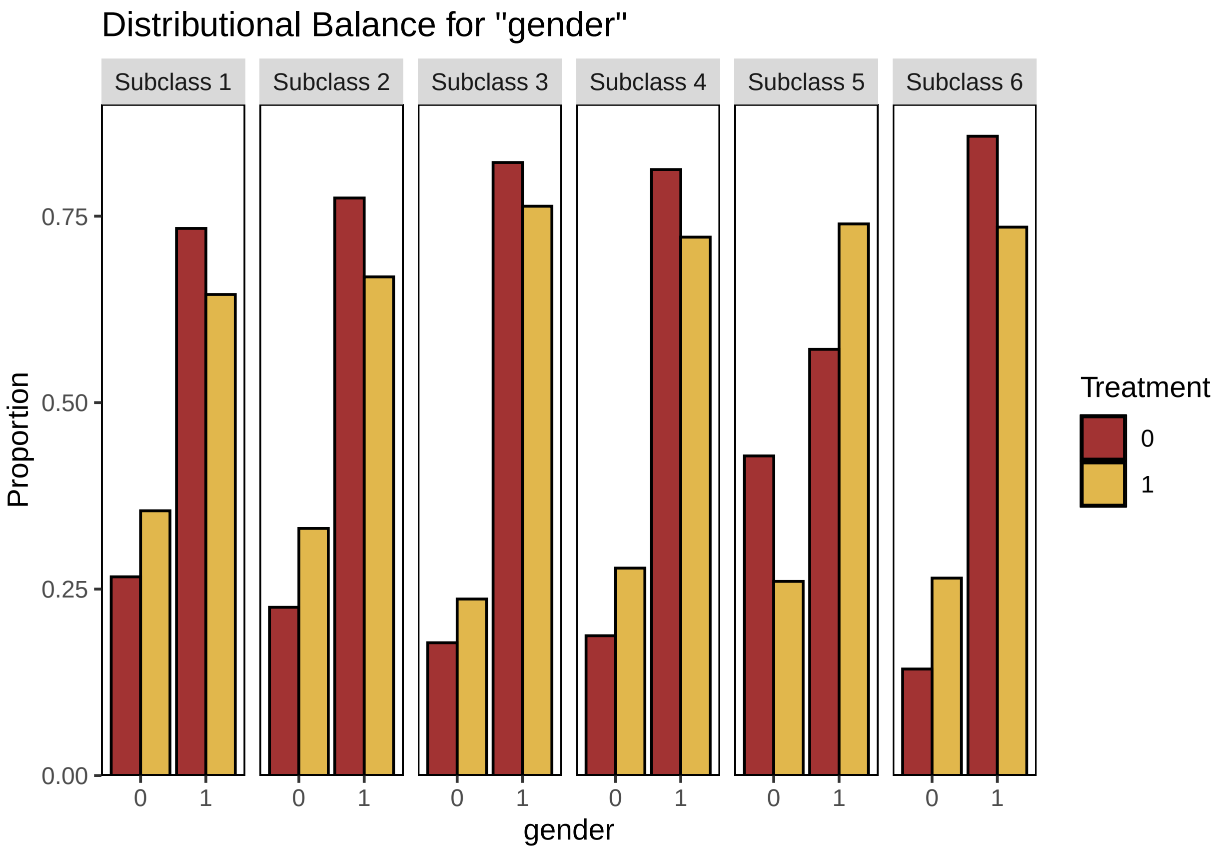
```
bal.plot(aaum.out1, var.name = "age", which = "both",
        colors = c("darkred", "goldenrod"))
```



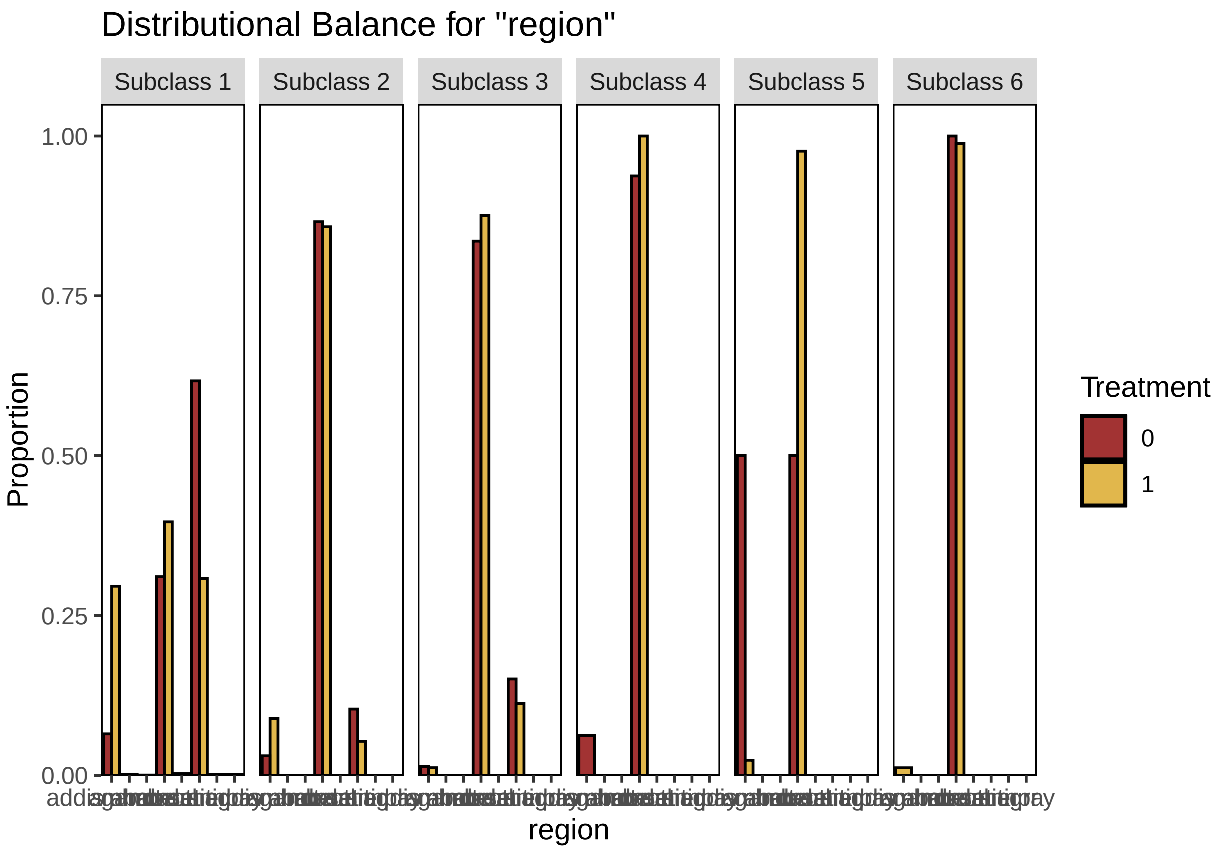

```
bal.plot(aaum.out1, var.name = "cgpa",
         colors = c("darkred", "goldenrod"))
```



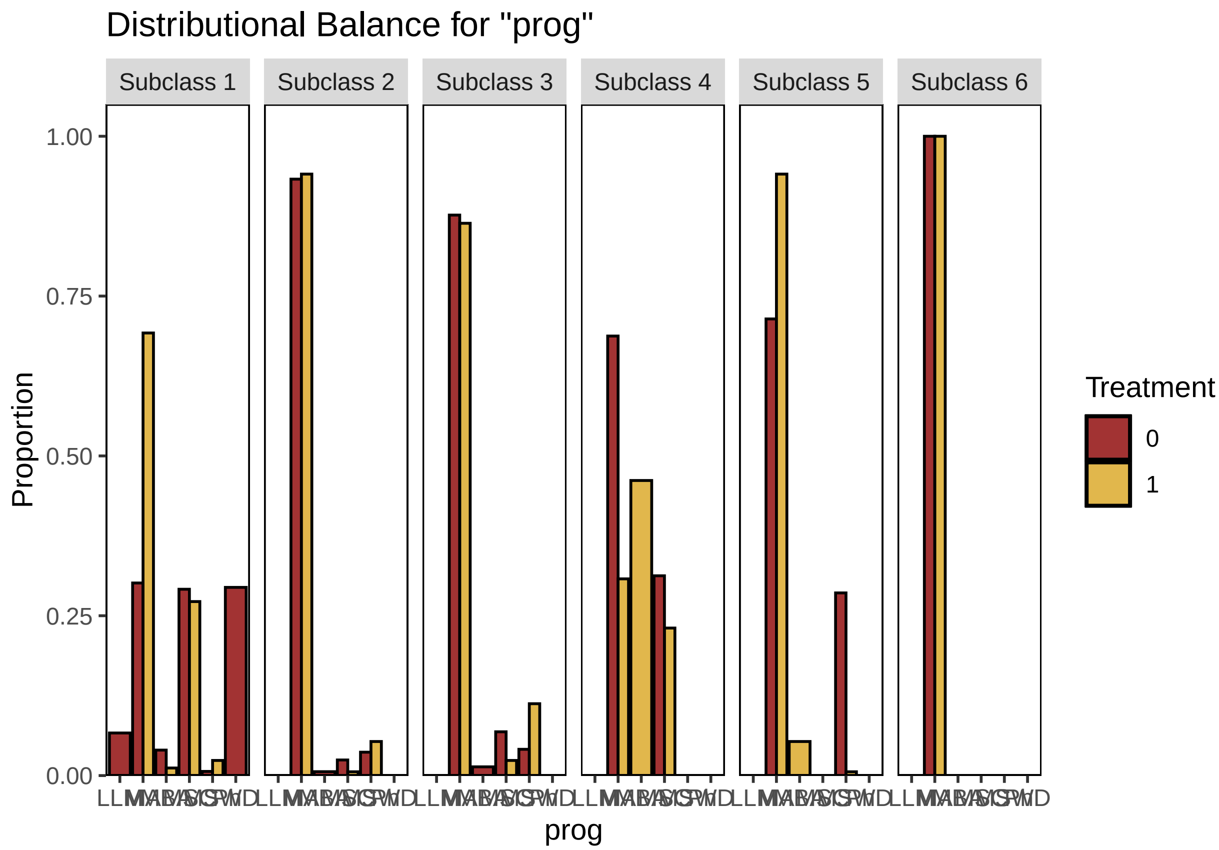

```r
bal.plot(aaum.out1, var.name = "gender",
         colors = c("darkred", "goldenrod"))
```



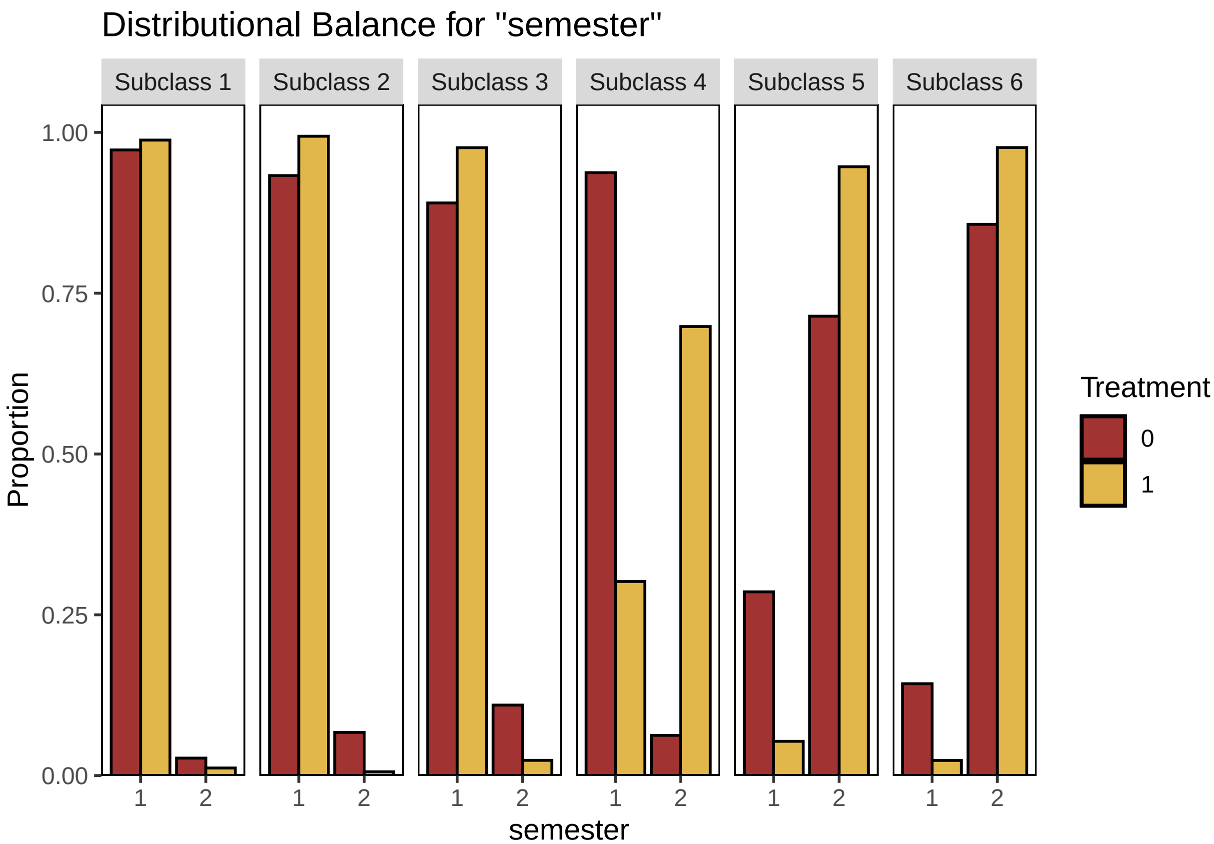

```
bal.plot(aaum.out1, var.name = "region",
         colors = c("darkred", "goldenrod"))
```




```
bal.plot(aaum.out1, var.name = "prog",
         colors = c("darkred", "goldenrod"))
```

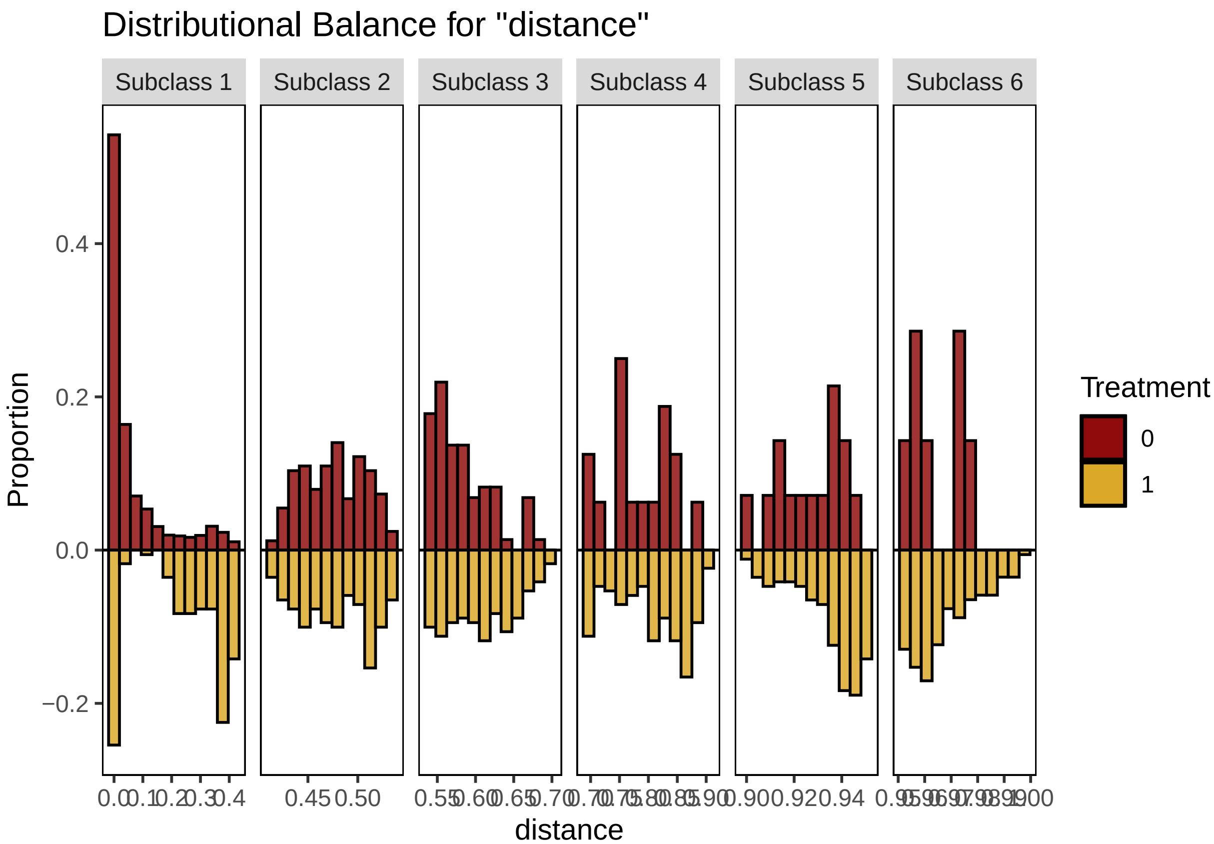



```
bal.plot(aaum.out1, var.name = "semester",
         colors = c("darkred", "goldenrod"))
```



Distributional balance of distance

```
bal.plot(aaum.out1, var.name = "distance",
         which = "both",
         type = "histogram",
          colors = c("darkred", "goldenrod"),
         mirror = TRUE)
```


Distributional Balance for "distance"
Subclass 1
Subclass 2
Subclass 3
Subclass 4
Subclass 5
Subclass 6
Proportion
0.4
0.2
0.0
−0.2
distance
0.45
0.50
0.90
0.92
0.94
Treatment
0
1

Estimating effect

```r
#Logistic regression on MatchIt output to estimate effect

aau_fit <- glm(cgpa ~ treat * (age + gender +  region + prog + semester),
               data = aaum.data, weights = weights)
summary(aau_fit)
```

```
##
## Call:
## glm(formula = cgpa ~ treat * (age + gender + region + prog +
##     semester), data = aaum.data, weights = weights)
##
## Coefficients: (7 not defined because of singularities)
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)          3.092153   0.105466  29.319  < 2e-16 ***
## treat               -0.100701   0.179582  -0.561 0.574999
## age                 -0.006858   0.001259  -5.446 5.47e-08 ***
## gender               0.120395   0.023264   5.175 2.39e-07 ***
## regionamhara         0.672775   0.528019   1.274 0.202683
## regiongambela       -0.151109   1.178126  -0.128 0.897948
## regionnot set       -0.001145   0.031564  -0.036 0.971074
## regionoromia         0.233930   0.446200   0.524 0.600118
## regionother          0.447760   0.039878  11.228  < 2e-16 ***
## regionsnnpr          0.565105   0.590100   0.958 0.338301
## regiontigray         0.524039   0.590561   0.887 0.374939
## progMA              -0.215927   0.089272  -2.419 0.015618 *
## progMBA             -0.344161   0.126482  -2.721 0.006536 **
## progMSC             -0.893776   0.091532  -9.765  < 2e-16 ***
## progMSW              0.152672   0.095361   1.601 0.109459
## progPhD              0.254056   0.096431   2.635 0.008456 **
## semester             0.252360   0.021998  11.472  < 2e-16 ***
## treat:age            0.007229   0.001981   3.649 0.000267 ***
## treat:gender        -0.030124   0.042458  -0.709 0.478058
## treat:regionamhara         NA         NA      NA       NA
## treat:regiongambela        NA         NA      NA       NA
## treat:regionnot set -0.096073   0.070684  -1.359 0.174162
## treat:regionoromia         NA         NA      NA       NA
## treat:regionother   -0.483664   0.124982  -3.870 0.000111 ***
## treat:regionsnnpr          NA         NA      NA       NA
## treat:regiontigray         NA         NA      NA       NA
## treat:progMA         0.334323   0.140162   2.385 0.017113 *
## treat:progMBA        0.595818   0.171993   3.464 0.000537 ***
## treat:progMSC        1.081107   0.122483   8.827  < 2e-16 ***
## treat:progMSW              NA         NA      NA       NA
## treat:progPhD              NA         NA      NA       NA
## treat:semester      -0.158511   0.043048  -3.682 0.000234 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.2536787)
##
##     Null deviance: 1414.4  on 4050  degrees of freedom
```

```
## Residual deviance: 1021.3  on 4026  degrees of freedom
## AIC: 10195
##
## Number of Fisher Scoring iterations: 2
```

```r
aaum_comp <- comparisons(aau_fit,
                     variables = "treat",
                     vcov = ~subclass,
                     newdata = subset(aaum.data, treat == 1),
                     wts = "weights")
summary(aaum_comp)
```

```
##
##   Term          Contrast Estimate Std. Error   z Pr(>|z|)  2.5 % 97.5 %
##  treat mean(1) - mean(0)    0.207     0.0625 3.3   <0.001 0.0841  0.329
##
## Columns: term, contrast, estimate, std.error, statistic, p.value, conf.low, conf.high
```

Checking balance

Assessing balance numerically

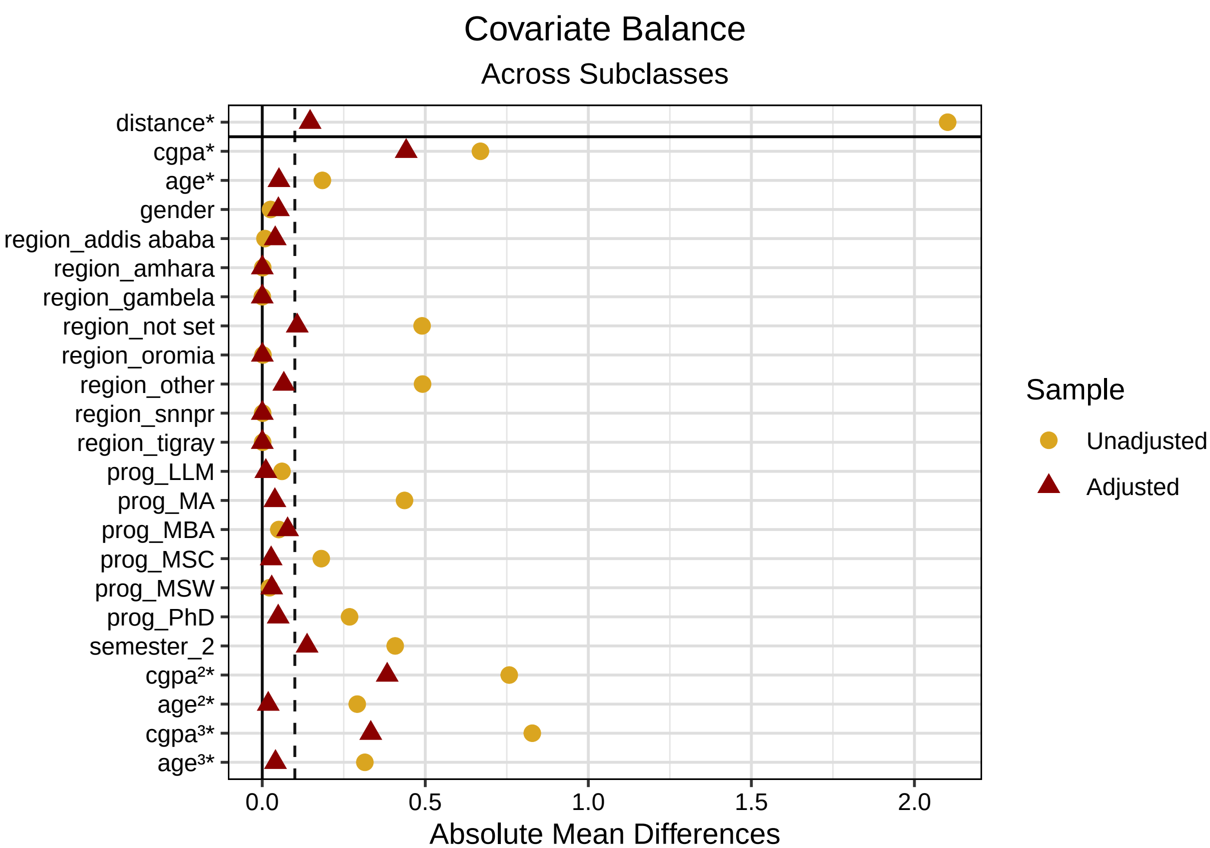
```
balance.table_aau <- bal.tab(aaum.out1, stats = c("c", "m"), un=TRUE,
        thresholds = c(cor = .1), poly = 3)
print(balance.table_aau)
```

```
## Balance measures across subclasses
##                          Type Diff.Un Diff.Adj
## distance             Distance  2.1020   0.1468
## cgpa                  Contin. -0.6691   0.4415
## age                   Contin.  0.1846  -0.0513
## gender                 Binary -0.0255  -0.0496
## region_addis ababa     Binary  0.0084  -0.0399
## region_amhara          Binary -0.0016  -0.0003
## region_gambela         Binary -0.0003  -0.0001
## region_not set         Binary  0.4902   0.1074
## region_oromia          Binary -0.0023  -0.0004
## region_other           Binary -0.4917  -0.0663
## region_snnpr           Binary -0.0013  -0.0002
## region_tigray          Binary -0.0013  -0.0002
## prog_LLM               Binary -0.0606  -0.0111
## prog_MA                Binary  0.4364   0.0388
## prog_MBA               Binary  0.0508   0.0778
## prog_MSC               Binary -0.1811  -0.0274
## prog_MSW               Binary  0.0223  -0.0291
## prog_PhD               Binary -0.2678  -0.0490
## semester_2             Binary  0.4078   0.1375
## cgpa²                 Contin. -0.7574   0.3833
## age²                  Contin.  0.2914   0.0184
## cgpa³                 Contin. -0.8282   0.3329
## age³                  Contin.  0.3147   0.0407
##
## Sample sizes by subclass
##              1   2   3   4   5   6  All
## Control 2762 164  73  16  14   7 3036
## Treated  169 169 169 169 169 170 1015
## Total   2931 333 242 185 183 177 4051
```

Assessing balance - covariate balance (Absolute Mean Differences)

```
love.plot(balance.table_aau,
          threshold =.1,
          line = FALSE,
          grid = TRUE,
          stars = "std",
```

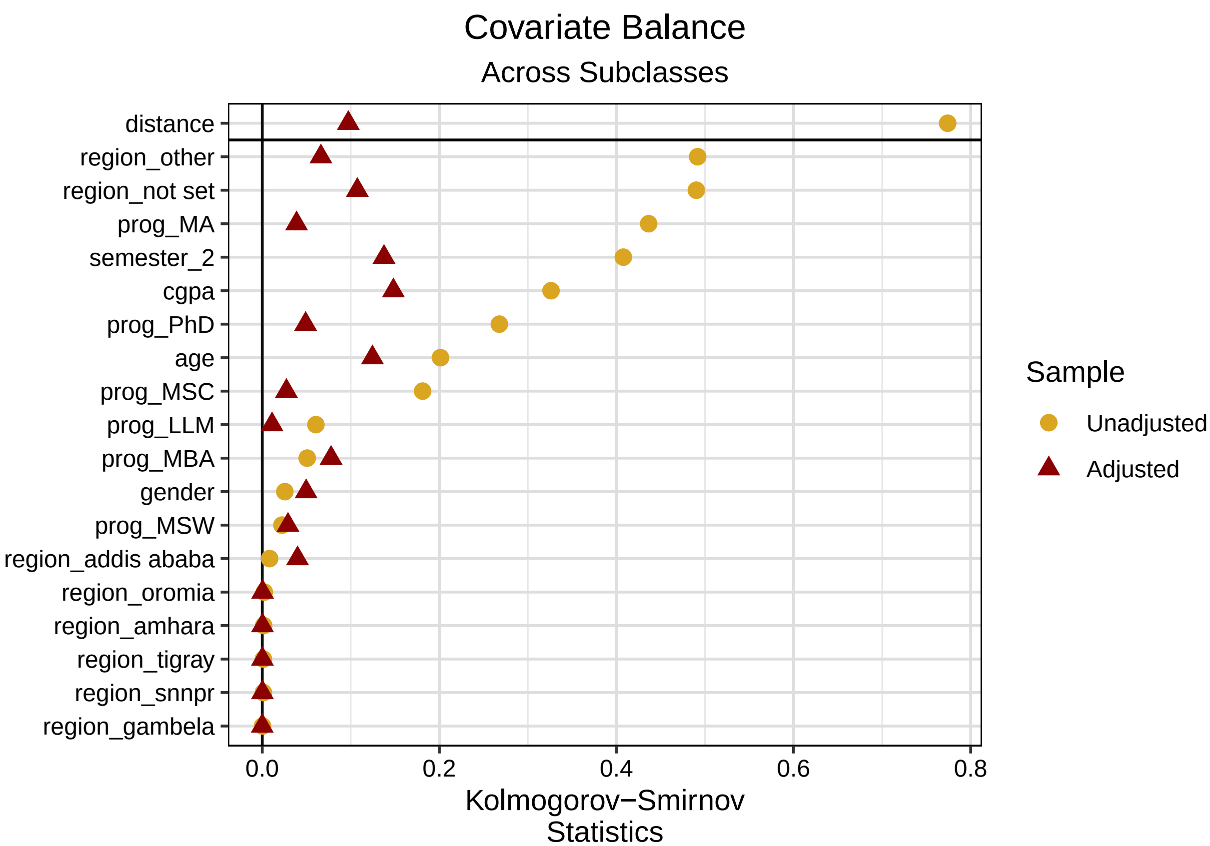
```
          labels = TRUE,
          abs= TRUE,
          colors = c("goldenrod", "darkred"),
          shapes = c("circle", "triangle"),
          size = 3,
          cex.main = 1.5,
          cex.sub = 1,
          cex.lab = 1,
          cex.axis = 1)
```



Assessing balance - Kolmogorov-Smirnov Statistics

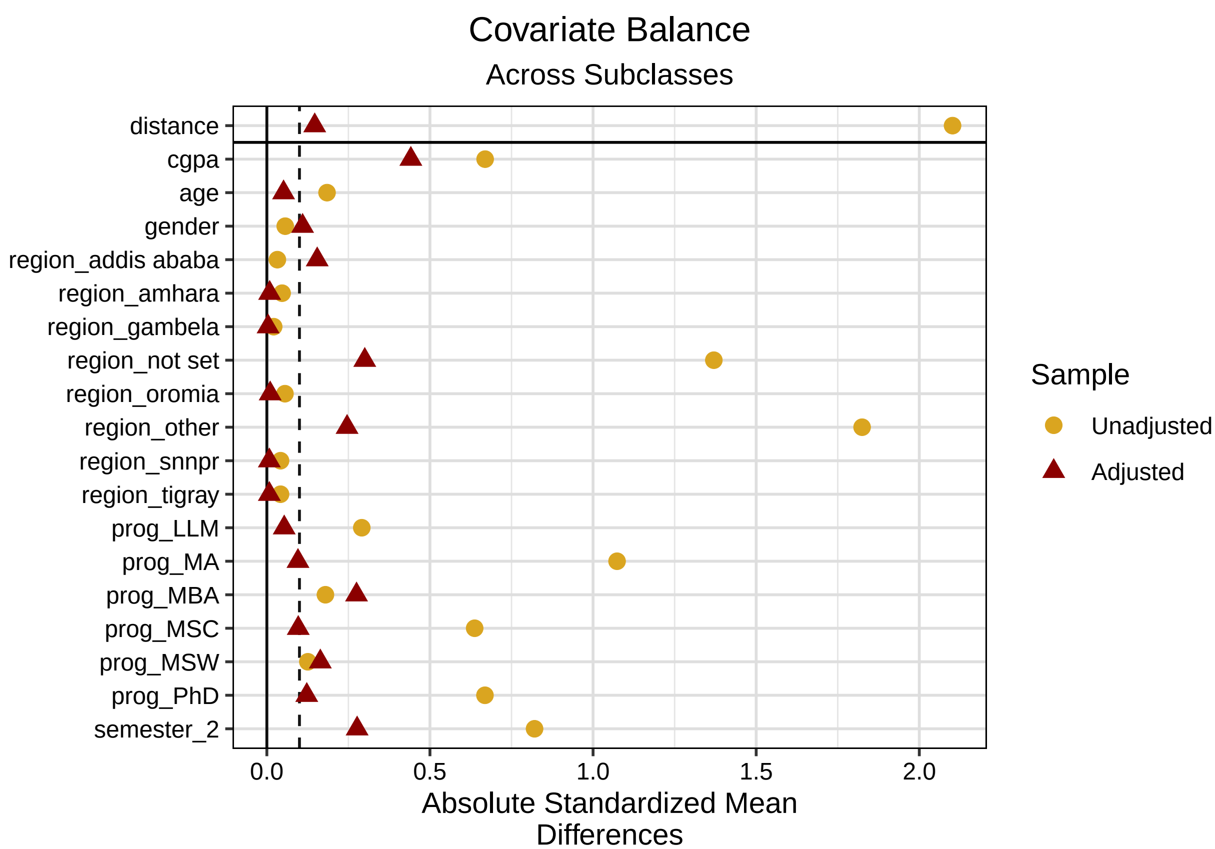
```
love.plot(aaum.out1, stats = c("c", "ks"),
          thresholds = c(cor = .1),
          abs = TRUE, wrap = 20,
          var.order = "unadjusted",
          line = FALSE,
          grid = TRUE,
          labels = TRUE,
          colors = c("goldenrod", "darkred"),
          shapes = c("circle", "triangle"),
          size = 3,
```

```
         cex.main = 1.5,
         cex.sub = 1,
         cex.lab = 1,
         cex.axis = 1)
```



Assessing balance - covariate blanace (Standardized Mean Difference)

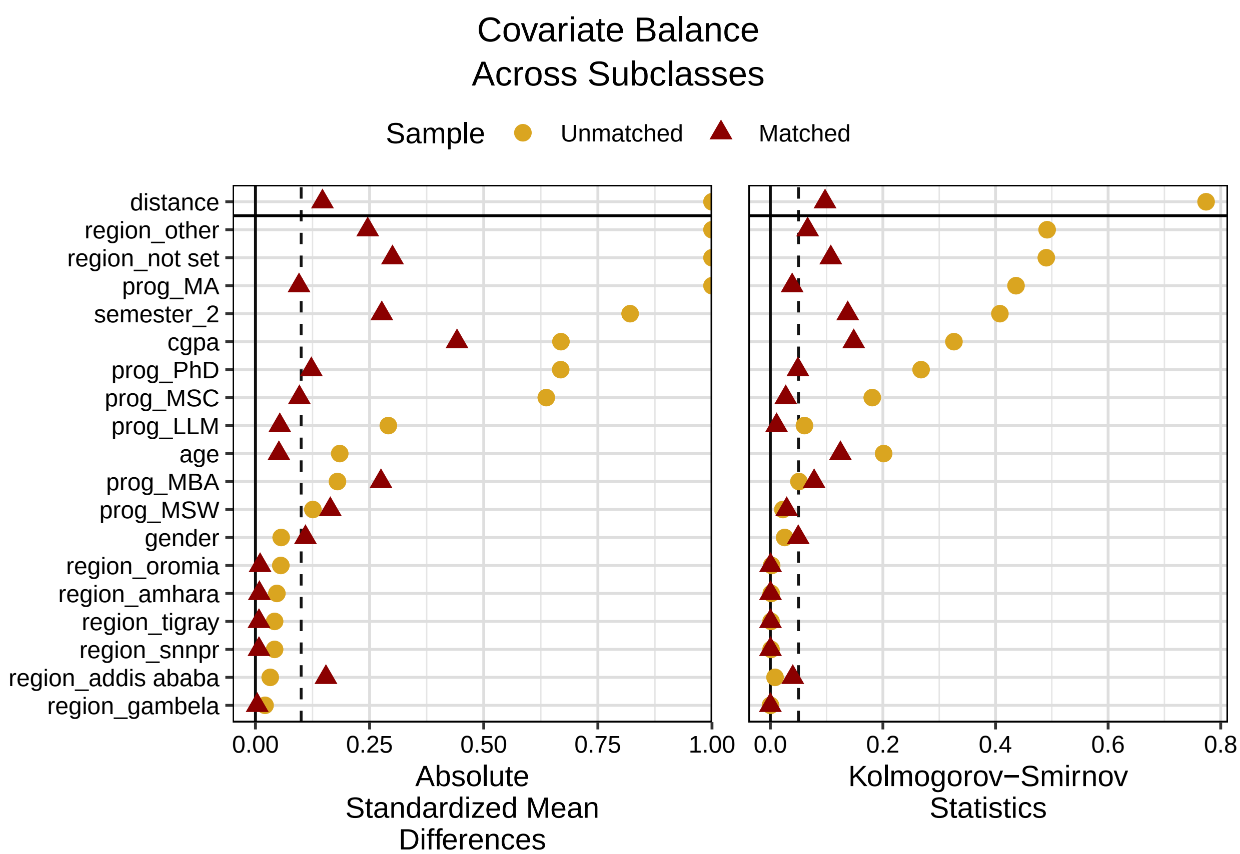
```
love.plot(aaum.out1, binary = "std", thresholds = c(m = .1),
         labels = TRUE,
         line = FALSE,
         grid = TRUE,
         abs= TRUE,
         colors = c("goldenrod", "darkred"),
         shapes = c("circle", "triangle"),
         size = 3,
         cex.main = 1.5,
         cex.sub = 1,
         cex.lab = 1,
         cex.axis = 1)
```



Assessing balance- covariate balance

(Standardized Mean Difference and Kolmogorov-Smirnov Statistics)

```
love.plot(aaum.out1, stats = c("mean.diffs", "ks.statistics"),
          threshold = c(m = .1, ks = .05),
          binary = "std",
          abs = TRUE,
          var.order = "unadjusted",
          var.names = NULL,
          limits = c(0, 1),
          grid = TRUE,
          wrap = 20,
          sample.names = c("Unmatched", "Matched"),
          position = "top",
          shapes = c("circle", "triangle"),
          colors = c("goldenrod", "darkred"),
          size = 3)
```


Covariate Balance
Across Subclasses
Sample
Unmatched
Matched
distance
region_other
region_not set
prog_MA
semester_2
cgpa
prog_PhD
prog_MSC
prog_LLM
age
prog_MBA
prog_MSW
gender
region_oromia
region_amhara
region_tigray
region_snnpr
region_addis ababa
region_gambela
0.00
0.25
0.50
0.75
1.00
Absolute
Standardized Mean
Differences
0.0
0.2
0.4
0.6
0.8
Kolmogorov−Smirnov
Statistics

Appendix VII

Qualitative Interview Instrument

Research question #2

1- What are the considerations in the deployment of EdTech for online learning?
   - *a. What is the decision-making process in selecting and deployment EdTech for online learning?*
   - *b. What have been the institutional and individual challenges learners, lecturers, and administrators face in integrating and leveraging EdTech?*

General *(all participants)*

1. Name
2. Institution
3. Department
4. Position
5. Years in position
   a. If student, level/year
6. Marital status
7. How many people in your household?
8. What is the highest degree you have earned?

General Technology use

1. Do you have an Internet connection at home?
2. Do you have an Internet connection at work/school?
3. What proportion of your salary do you pay for Internet access?
4. Do you own a personal computer?
5. Do you own a smartphone?
6. How often are you online?
7. What are some of the things you do online?

Digital literacy

1. Digital/technology aptitude (self-rating with prompts)?
   Professional- IT accreditation, programming, and coding experience
   Expert – basic+ average +can troubleshoot issues, understands/knows about algorithms, bandwidth,
   Average – basic + understands can use social media, enterprise software without difficulty
   Basic – basic operation of word processing and getting online)
2. How would you rate your expertise in using technology in everyday life?
3. How would you rate your expertise in using technology in an education setting?
4. Tell me a little about what you find easy?
5. Tell me a little about what you find challenging?
6. How familiar are you with the technology and digital tools for education?
7. How do you learn about new tools and technologies?

Role in institution
Leadership
Background

1. Tell me about your teaching experience?
2. Have you taught an online course?
3. Have you taken an online course?
4. To what extent is technology integrated into daily tasks in the office?
5. How do you keep up with the latest technology/digital systems?

Technology

1. Who proposes new technology for the university administration?
2. Who proposes new technology for instruction?
3. Who proposes new technology related to online learning
4. What is the process for offering new technology for acquisition?
5. What is the process for requesting new technology acquisition?
6. Who is engaged in the discussion of adopting new technology?
7. What are some of the considerations in adopting new technology?
8. How is the Communication and Technology Office (CTO) involved?
9. Is there engagement of non-university personnel?
    a. Who is engaged?
    b. What is their role?
10. Who is responsible for making the final decision on adopting technology?

Student
Background

1. Tell me a little about your educational background before joining the online program?
2. Have you taken an online class before this program?
3. Why did you decide to take an online class?
4. What are your career goals?
5. How does this program help you reach those goals?

Experience with online learning

1. How would you describe your online learning experience?
2. What are some of the areas you found easy?
3. What are some of the areas you found challenging?
4. How much many hours per week do you spend on online learning?
5. How would you compare your online learning experience with classroom instruction?
6. What type of support do you receive from the institution during this course?
7. What grade are you expecting to earn in the course?
8. What do you think contributed to your (success/failure)?
9. Would you recommend online learning to other students?

Technology

1. Tell me a little about the learning platform for your program?
2. What device do you use for online learning?
3. Where do you access the Internet to participate in the online course?

4. How did you find the registration process?
5. How did you find the delivery of instructional materials?
6. How often did you encounter technical difficulties while using the system?
7. How often did you not use the system because it was down/malfunctioning?

Online learning instructors

Background

1. Tell me a little about your teaching experience?
2. How long have you taught online?
3. What are your thoughts on online learning?
4. What is your prediction for the future of online learning at your institution?

Online instruction

1. Did you receive training on online training?
2. Were you engaged in developing the module for the online course you are currently teaching?
3. Are you the instructor for the campus-based course of this online course?
4. Were you engaged in the decision to adopt the online learning system?
5. How much training did you receive on the system before you started teaching?
6. Do you receive periodic skills upgrade?
7. What features do you find helpful?
8. What features do you find challenging?
9. How often did you integrate technology in your teaching before you started teaching online?

Online learning administrator (ICT)

Background

1. Tell me a little about your educational background prior?
2. Tell me about your training/experience in tech?
3. How do you keep your technology skills current?

Technology

11. Do you know who is in charge of proposing new technology for the university?
12. Who proposes new technology for instruction?
13. Who proposes new technology related to online learning
14. What is the process for offering new technology for acquisition?
15. What is the process for requesting new technology acquisition?
16. Are you engaged in the discussion of adopting new technology?
17. Who is responsible for making the final decision on adopting technology?
18. What do you think are some of the considerations in adopting new technology?
19. What is your unit's relationship with the Communication and Technology Officer (CTO) involved?

REFERENCE

Aalangdong, E. (2022). *An assessment of the influence of the tertiary education institution (TEIs) policy framework on distance education delivery in Ghan*a [Unpublished dissertation]. University of Ghana.

AAU Faculty I. (2022, December 21). [Personal communication].

AAU Faculty II. (2023, January 10). [Personal communication].

AAU Technology. (2023, March 8). [Personal communication].

Abrokwaa, C. (2017). Colonialism and the Development of Higher Education. In E. Shizha & N. Makuvaza (Eds.), *Re-thinking postcolonial education in Sub-Saharan Africa in the 21st Century: Post-millennium development goals* (pp. 203–220). SensePublishers. https://doi.org/10.1007/978-94-6300-962-1_12

Acemoglu, D., & Autor, D. (2012). What Does Human Capital Do? A Review of Goldin and Katz's The Race between Education and Technology. *Journal of Economic Literature*, 50(2), 426–463. https://doi.org/10.1257/jel.50.2.426

Acquah, E. H. K., & Budu, J. M. (2017). The University of Ghana: A "premier" university in national development. In *Flagship universities in Africa*. Palgrave Macmillan.

Addis Ababa University. (2018, January 3). *School of Commerce Observes 75th Anniversary*. http://www.aau.edu.et/blog/school-of-commerce-observes-75th-anniversary/

Affordability Internet, A. (2019). *Affordability report 2019: Regional Snapshot Africa*. Alliance for Affordability Internet.

Africa telecom map 2022. (2022). [Map]. https://africa-map-2022.telegeography.com/

Agger, B. (1991). Critical theory: Poststructuralism, postmodernism: Their sociological relevance. *Annual Review of Sociology*, 17, 105–131.

Ahmed, H. (2006). Addis Ababa University: Fifty-three years on an insider's view. *Cahiers d'études Africaines*, 182, 291–312.

Ahmed, S. A., Cruz, M., Go, D. S., Maliszewska, M., & Osorio-Rodarte, I. (2014). *How Significant is Africa's Demographic Dividend for its Future Growth and Poverty Reduction?* The World Bank. https://doi.org/10.1596/1813-9450-7134

Alexander, N. C. (2001). Paying for Education: How the World Bank and the International Monetary Fund Influence Education in Developing Countries. *Peabody Journal of Education*, 76(3–4), 285–338. https://doi.org/10.1080/0161956X.2001.9682002

Alghazo, A. M. (2005). Comparing effectiveness of online and traditional teaching using students' final grades. *Online Journal for Workforce Education and Development*, 1(3), 12.

Ali, W. (2019). Assessment on factors causing female students attrition at Haramaya University, Ethiopia. *Scientific Research Journal*, 7(11).

Ally, M. (2004). Foundations of educational theory for online learning. *Theory and Practice of Online Learning*, 2, 15–44.

Alozie, N. O., & Akpan-Obong, P. (2017). The digital gender divide: Confronting obstacles to women's development in Africa. *Development Policy Review*, 35(2), 137–160.

Altbach, P. G., Reisberg, L., & Rumbley, L. E. (2009). *Trends in global higher education: Tracking an academic revolution.* UNESCO.

Altshuler, A., & Luberoff, D. (2003). *Mega-Projects*. Brookings Institution Press; JSTOR. http://www.jstor.org/stable/10.7864/j.ctvb9384v

Amedzro, A. A. (2005). *Globalisation, non-formal education and rural development*. Ghana University Press.

Appiah-Nyamekye Sanny, J. (2020). Unemployment and education are Ghanaian youth's most important problems. *Afrobarometer Dispatch No. 382*; p. 9. Afrobarometer.

Apple. (2023). *Apple Pay*. Apple Pay. https://www.apple.com/apple-pay/

Appleton, S. (2000). Education and health at the household level in Sub-Saharan Africa. CID *Working Papers Series*. Cambridge: Harvard University. https://dash.harvard.edu/handle/1/39468340

Asante, M. K. (1994). The African aesthetic: Keeper of the traditions. In K. Welsh-Asante (Ed.), *Location Theory and African Aesthetics*. Greenwood Press.

Asfaw, A. (2012). Gender inequalities in Tertiary education in Ethiopia: Mediating the transition to university through the development of adaptive competencies. *Working Paper No. 5; Global Scholars Program Working Papers Series*, p. 24. Brookings Institute. https://www.brookings.edu/wp-content/uploads/2018/03/gender-inequalities-in-tertiary-education-in-ethiopia.pdf

Asher, R. E., & Mason, E. S. (1973). *The World Bank since Bretton Woods*. Brookings Institution.

Assié-Lumumba, N. T. (2008). Higher education as an African public sphere and the university as a site of resistance and claim of ownership for the national project. *CODESRIA*, 31.

Asunka, S. (2008). Online learning in higher education in Sub-Saharan Africa: Ghanaian university students' experiences and perceptions. *The International Review of Research in Open and Distributed Learning*, 9(3). https://doi.org/10.19173/irrodl.v9i3.586

Atuahene, F., & Owusu-Ansah, A. (2013). A descriptive assessment of higher education access, participation, equity, and disparity in Ghana. *SAGE Open*, 3(3), 2158244013497725. https://doi.org/10.1177/2158244013497725

AWS. (2023). *What is 5G?* Amazon Web Services. https://aws.amazon.com/what-is/5g/

Ayalew, E. (2017). Once a flagship always a flagship?: Addis Ababa University in perspective. In D. Teferra (Ed.), *Flagship universities in Africa* (pp. 91–137). Palgrave Macmillan.

Ayalew, S. (1989). Some trends in regional disparities in primary school participation in Ethiopia. *Ethiopian Journal of Education*, 11(1), 25–50.

Ayelazuno, J. A. (2014). Neoliberalism and Growth without Development in Ghana: A Case for State-led Industrialization. *Journal of Asian and African Studies*, 49(1), 80–99. https://doi.org/10.1177/0021909613478787

Barouni, M., & Broecke, S. (2014). The Returns to Education in Africa: Some New Estimates. *The Journal of Development Studies*, 50(12), 1593–1613. https://doi.org/10.1080/00220388.2014.936394

Bartlett, L., & Vavrus, F. (2017). Comparative Case Studies: An Innovative Approach. Nordic *Journal of Comparative and International Education* (NJCIE), 1(1). https://doi.org/10.7577/njcie.1929

Baxter, J., Callaghan, G., & McAvoy, J. (2018). The context of online teaching and learning: Neoliberalism, marketization and online teaching. In J. Baxter, G. Callaghan, & J. McAvoy (Eds.), *Creativity and Critique in Online Learning: Exploring and Examining Innovations in Online Pedagogy* (pp. 13–29). Springer International Publishing. https://doi.org/10.1007/978-3-319-78298-0_2

Bazeley, P. (2018). *Complementary analysis of varied data sources.* SAGE Publications.

BBC. (2016, January 6). *E-learning for Africa held back by power shortage*. BBC News. https://www.bbc.com/news/business-35177144

Becker, G. S. (1971). *The economics of discrimination* (2nd ed.). University of Chicago Press.

Becker, G. S. (1985). Human capital, effort, and the sexual division of labor. *Journal of Labor Economics*, 3(1), S33–S58. JSTOR. http://www.jstor.org/stable/2534997

Becker, G. S. (1993). *Human capital: A theoretical and empirical analysis, with special reference to education* (Third Edition). University of Chicago.

Becker, G. S. (2002). The age of human capital. In E. P. Lazear (Ed.), *Education in the Twenty First Century* (pp. 3–8). Hoover Institution Press.

Belohlav, K. (2016). *Investing in women and girls for a gender dividend*. Population Reference Bureau.

Benjamin, R. (2020). Race after technology: Abolitionist tools for the new Jim code. *Social Force*s, 98(4), 1–3. https://doi.org/10.1093/sf/soz162

Bennell, P. (1996). Rates of return to education: Does the conventional pattern prevail in sub-Saharan Africa? *World Developmen*t, 24(1), 183–199. https://doi.org/10.1016/0305-750X(95)00115-S

Bennell, P. (1998). Rate of return to education in Asia: A review of the evidence. *Education Economics,* 6(2), 107–120. https://doi.org/10.1080/09645299800000010

Bernard, R., Abrami, P., Lou, Y., Borokhoviski, E., Wade, A., Wozney, L., & Haung, B. (2004). How does distance education compare with classroom instruction: A meta-analysis of the empirical literature. *Review of Educational Research*, 74(3), 379–439.

Biebricher, T. (2018). *The political theory of neo-liberalism*. Stanford University Press.

Bishaw, A., & Lasser, J. (2012). Education in Ethiopia: Past, Present and Future Prospects. *African Nebula*. 5

Blanchard, E., Razaki, R., & Frasson, C. (2005). C*ross-cultural adaptation of e-learning contents: A methodology.*

Bolukbasi, T., Chang, K.-W., Zou, J. Y., Saligrama, V., & Kalai, A. T. (2016). Man is to computer programmer as woman is to homemaker? Debiasing word embeddings. *Advances in Neural Information Processing Systems*, 29.

Brazauskas, R. (2016, December). *Matching versus Regression in Observational Studies.* Medical College of Wisconsin: Datum.

Brugger, F., & Gehrke, C. (2018). Skilling and deskilling: Technological change in classical economic theory and its empirical evidence. *Theory and Society*, 47(5), 663–689. https://doi.org/10.1007/s11186-018-9325-7

Buolamwini, J., & Gebru, T. (2018). Gender shades: Intersectional accuracy disparities in commercial gender classification. *Proceedings of the 1st Conference on Fairness, Accountability and Transparency*, PMLR 81:77-91.

Burnette, J. (1997). An investigation of the female-male wage gap during the Industrial Revolution in Britain. *The Economic History Review*, 50(2), 257–281. JSTOR. http://www.jstor.org/stable/2599060

Caffentzis, G. (2002). Neoliberalism in Africa, apocalyptic failures and business as usual practices. *Alternatives: Turkish Journal of International Relations*, 1(3), 88–104.

Caliendo, M., & Kopeinig, S. (2005). Some practical guidance for the implementation of propensity score matching. *Discussion Paper No. 1588*, 32.

Chukwuere, J. E., Mavetera, N., & Mnkandla, E. (2018). Student's perception on culture-oriented e-learning system: An empirical study. In F. Altınay (Ed.), *Open and Equal Access for Learning in School Management*. InTechopen. https://doi.org/10.5772/intechopen.71586

CIPSEA. (2022). *Bridging the gender digital divide is critical for achieving digital rights in Africa*. Collaboration on International ICT Policy for East and Southern Africa. https://cipesa.org/2022/06/bridging-the-gender-digital-divide-is-critical-for-achieving-digital-rights-in-africa/

Corn, J. O., Oliver, K. M., Hess, C. E., Halstead, E. O., Argueta, R., Patel, R. K., Tingen, J., & Huff, J. D. (2010). A computer for every student and teacher: Lessons learned about planning and implementing a successful 1:1 learning initiative in schools. *Educational Technology*, 50(6), 11–17. JSTOR. http://www.jstor.org/stable/44429870

Creswell, J. W., & Creswell, J. D. (2018). *Research Design: Qualitative, quantitative, and mixed methods approaches*. Sage Publications

Cutrell, E. (2011). Context and design in ICT for global development. *UN Chronicle*, XLVIII(3). https://www.un.org/en/chronicle/article/context-and-design-ict-global-development

Daniel, D., Robert, O.-B., & Samuel, A. (2020). A philosophical outlook on Africa's higher education in the Twenty-First century: Challenges and prospects. In K. Tirri & A. Toom (Eds.), *Pedagogy in Basic and Higher Education—Current Developments and Challenges*. IntechOpen. https://doi.org/10.5772/intechopen.86885

Davies, B., & Bansel, P. (2007). Neoliberalism and education. *International Journal of Qualitative Studies in Education*, 20(3), 247–259.

Department of Distance Learning. (2023, March 2). [Personal communication].

Dews, F. (2019). *Africa's changing demographics*. https://www.brookings.edu/blog/brookings-now/2019/01/18/charts-of-the-week-africas-changing-demographics/

Diagne, A., & Diene, B. (2011). Estimating returns to higher education: A survey of models, methods and empiricalevidence. *Journal of African Economies*, 20(suppl_3), iii80–iii132. https://doi.org/10.1093/jae/ejr021

Diebolt, C., & Hippe, R. (2019). The long-run impact of human capital on innovation and economic development in the regions of Europe. *Applied Economics*, 51(5), 542–563. https://doi.org/10.1080/00036846.2018.1495820

Ding, P., & Li, F. (2018). Causal inference: A Missing data perspective. *Statistical Science*, 33(2). https://doi.org/10.1214/18-STS645

Distance Learning/Sakai. (2021, July 27). [Personal communication].

Drako, Samuel F. (1985). *An historical inquiry into the development of higher education in Ghana 1948-1984: A study of the major factors that have controlled and inhibited the development of the universities of Ghana* [Unpublished dissertation]. https://digital.library.unt.edu/ark:/67531/metadc330942/m2/1/high_res_d/1002715844-Darko.pdf

Drummond, P., Thakoor, V., & Yu, S. (2014). Africa rising harnessing the demographic dividend. *International Monetary Fund*, Africa Department.

Dutta, S. J., Knafo, S., & Lovering, I. A. (2022). Neoliberal failures and the managerial takeover of governance. *Review of International Studies*, 48(3), 484–502. https://doi.org/10.1017/S0260210521000619

Edgerton, J., Roberts, L., & Below, S. von. (2012). Education and quality of life. In *Handbook of Social Indicators and Quality of Life Research* (pp. 265–296). https://doi.org/10.1007/978-94-007-2421-1_12

EdTech20. (2017). *Edtech 2.0: The ultimate guide to Edtech*. https://medium.com/@edtech2/the-ultimate-guide-to-edtech-88b9f984ada0

Education Commission. (2015). *The learning generation: Investing in education for a changing world*. International Commission on Financing Global Education Opportunity.

Edwin, M., & Yaw, A. N. (2016). The Effectiveness of Distance Education in Ghana. Science *Journal of Applied Mathematics and Statistics*, 4(4), 159–167.

eLearning Africa. (2020). *The effect of Covid-19 on education in Africa and its implications for the use of technology: A survey of the experience and opinions of educators and technology specialists* (p. 81) [Survey report]. ELearning Africa.

Eubanks, V. (2018). *Automating inequality: How high-tech tools profile, police, and punish the poor*. St. Martin's Press.

Faidley, J. (2018). *Comparison of learning outcomes from online and face-to-face accounting course* [Unpublished dissertation,]. East Tennessee State University, School of Graduate Studies.

Fanon, F. (1963). *The wretched of the earth*. Grove Press.

Faturoti, B. (2022). Online learning during COVID19 and beyond: A human right based approach to internet access in Africa. *International Review of Law, Computers & Technology*, 36(1), 68–90.

Fendler, R. J., Ruff, C., & Shrikhande, M. M. (2018). No significant difference—Unless you are a jumper. *Online Learning*, 22(1), 39–60. https://doi.org/10.24059/olj.v22i1.887

Ferraro, v. (2008). Dependency theory: An introduction. In G. Secondi, *The development of economics reader.* Routledge.

Flick, U. (2007). Qualitative research designs. In U. Flick (Ed.), *Designing qualitative research* (pp. 36–50). SAGE.

Flybjerg, B., Skamris Holm, M. K., & Buhl, S. L. (2004). What Causes Cost Overrun in Transport Infrastructure Projects? *Transport Reviews*, 24(1), 3–18. https://doi.org/10.1080/0144164032000080494a

Flyvbjerg, B. (2005). Design by Deception: The politics of megaproject approval. Harvard *Design Magazine*, 22, 50–59.

Foo, C., Cheung, B., & Chu, K. (2021). A comparative study regarding distance learning and the conventional face-to-face approach conducted problem-based learning tutorial during the COVID-19 pandemic. *BMC Medical Education*, 21(1), 141. https://doi.org/10.1186/s12909-021-02575-1

Foucault, M. (1980). *Power/knowledge: Selected interviews and other writings 1972-1977* (1st ed.). Vintage.

Fox, L. (2019). *Foresight Africa: Three myths about youth employment in Africa and strategies to realize the demographic dividend*. Brookings Institution, Africa Growth Initiative.

Fukui, R., Arderne, C. J., & Kelly, T. (2019, November). *Africa's connectivity gap: Can a map tell the story?* The World Bank Blogs. https://blogs.worldbank.org/digital-development/africas-connectivity-gap-can-map-tell-story

Gakio, K. (2006). *African tertiary institutions connectivity survey*. International Development Centre of Canada.

Gelman, A., & Hill, J. (2006). *Data analysis using regression and multilevel/hierarchical models*. Cambridge University Press; Cambridge Core. https://doi.org/10.1017/CBO9780511790942

Goldman Sachs. (2023). *The potentially large effects of artificial intelligence on economic growth*. Goldman Sachs. https://www.goldmansachs.com/insights/pages/stability-ai-ceo-says-ai-will-prove-more-disruptive-than-the-pandemic.html

Goldthorpe, J. H. (2001). Causation, statistics, and sociology. *European Sociological Review*, 17(1), 1–20. https://doi.org/10.1093/esr/17.1.1

González-Gómez, F., Guardiola, J., Martín-Rodríguez, Ó., & Montero-Alonso, M. Á. (2012). Gender differences in e-learning satisfaction. *Computers & Education*, 58(1), 283–290.

Greco, J. (2020). Introduction: Testimony and the transmission of knowledge. In *The Transmission of Knowledge* (pp. 1–24). Cambridge University Press. https://doi.org/10.1017/9781108560818.002

Grimm, M. (2003). Family and economic growth: A review. *Mathematical Population Studies*, 10(3), 145–173. https://doi.org/10.1080/08898480306719

Gujarati, D. N. (2003). *Basic econometrics* (4th ed). McGraw Hill.

Hammarberg, K., Kirkman, M., & Lacey, S. (2016). Qualitative research methods: When to use them and how to judge them. *Human Reproduction*, 31(3), 498–501.

Hapte, A. (1961). A brief review of the history of the University College of Addis Ababa. *University College Review*, 1(1), 25–3. JSTOR. http://www.jstor.org/stable/41965667

Hayashi, P., Abib, G., & Hoppen, N. (2019). Validity in qualitative research: A processual approach. *The Qualitative Report*, 24(1), 98–112.

Higgs, P. (2009). Towards an indigenous African educational discourse: A philosophical reflection. In S. Majhanovich, C. Fox, & A. P. Kreso (Eds.), *Living Together: Education and Intercultural Dialogue* (pp. 159–172). Springer Netherlands. https://doi.org/10.1007/978-1-4020-9816-1_10

Huawei. (2020). *The Global Connectivity Index*. Huawei.

Huff, R. (n. d.). *Human capital*. In Encyclopedia Britannica.

Hurt, S. R. (n.d.). *Washington Consensus*. In Encyclopedia Britannica. Retrieved February 6, 2023, from https://www.britannica.com/topic/Washington-consensus

Husain, I. (1993). *Poverty and structural adjustment: The African case* (Human Resource #9; p. 25). The World Bank. https://documents1.worldbank.org/curated/en/517231468741855925/pdf/multi0page.pdf

Huyer, S., & Hafkin, N. (2018). *Cinderella or Cyberella? Empowering Women in the Knowledge Society*. Lynne Rienner Publishers

IFC. (2022). *Women and online learning in emerging markets*. [Research report]. The World Bank. https://www.ifc.org/wps/wcm/connect/b6a2e805-3c88-4145-bee7-14824ded31c8/Report_Women+and+Online+Learning+in+Emerging+Markets.pdf?MOD=AJPERES&CVID=o7uQanh

IFC/The World Bank. (2019). *Digital skills in Sub-Saharan Africa: Spotlight on Ghana*. [Research report]. The World Bank.

ILO. (2019). *Skills and jobs mismatches in low- and middle-income countries*. International Labour Organization.

ILO. (2023). *Labour underutilization*. In ILO glossary. International Labour Organization.

ILOSTAT. (2023a). *Inactivity rate by sex, age and education (%)*—Annual [Data set]. International Labour Organization.

ILOSTAT. (2023b). *SDG indicator 8.5.2—Unemployment rate (%)—Annual* [Data set]. International Labour Organization.

ILOSTAT. (2023c). *Share of youth not in employment, education or training (NEET)* [Data set]. International Labour Organization.

Imbens, G. W., & Rubin, D. B. (2015). *Causal inference for statistics, social, and biomedical sciences.* Cambridge University Press. https://doi.org/10.1017/CBO9781139025751.001

IMF. (1994, March). The East Asian miracle: Building a basis for growth. *Finance & Development*, 4.

Infrastructure finance. (2022, August). [Organization]. The World Bank Group. https://www.worldbank.org/en/topic/financialsector/brief/infrastructure-finance

Jiang, S., Schenke, K., Eccles, J. S., Xu, D., & Warschauer, M. (2018). Cross-national comparison of gender differences in the enrollment in and completion of science, technology, engineering, and mathematics Massive Open Online Courses. *PLoS One,* 13(9).

Johnson, R. (2011). Gender differences in e-learning: Communication, social presence, and learning outcomes. *Journal of Organizational and End User Computing*, 23(1), 79–94.

Jowi, J. O., Obamba, M., Sehoole, C., Oanda, O., Alabi, G., & Barifaijo, M. (2013). *Governance of higher education, research and innovation in Ghana, Kenya and Uganda* (p. 133). OECD. https://www.oecd.org/sti/Governance%20of%20higher%20education%20research%20and%20innovation%20in%20Ghana%20Kenya%20and%20Uganda.pdf

Joy, S., & Kolb, D. A. (2009). Are there cultural differences in learning style? *International Journal of Intercultural Relations,* 33(1), 69–85. https://doi.org/10.1016/j.ijintrel.2008.11.002

Kauffman, H. (2015). A review of predictive factors of student success in and satisfaction with online learning. *Research in Learning Technology*, 23. https://doi.org/10.3402/rlt.v23.26507

Kigotho, W. (2023, March 23). Do universities in the Sub-Sahara serve the public good? *University World News.* https://www.universityworldnews.com/post.php?story=2023032219052481

Kim, J. Y. (2018, June 18). The human capital gap. *Foreign Affairs*. https://www.foreignaffairs.com/articles/2018-06-14/human-capital-gap

Kindberg-Hanlon, G. (2021, February 10). *The technology-employment trade-off: Industry, automation, and income effects* [Organization blog]. World Bank Blogs. https://blogs.worldbank.org/developmenttalk/technology-employment-trade-industry-automation-and-income-effects

Kingdon, G., Patrinos, H., & Colclough, C. (2010). The changing pattern of wage returns to education and its implications. *Development Policy Review*, 28, 733–747. https://doi.org/10.1111/j.1467-7679.2010.00507.x

Kokutse, F. (2020). More graduates, but what about skills and employment? *University World News*.

Kothari, U. (2006). Editorial: Critiquing "race" and racism in development discourse and practice. *Progress in Development Studies*, 6(1), 1–7.

Kronke, M. (2020). Afrobarometer policy paper no. 66: Africa's digital divide and the promise of elearning. *Afrobarometer*.

Kuttner, R. (2019). Neoliberalism: Political success, economic failure. *The American prospect*.

Kwakwa, V. (2023, March). *Accelerating gender equality: Let's make digital technology work for all* [Organization blog]. World Bank Blogs. https://blogs.worldbank.org/africacan/accelerating-gender-equality-lets-make-digital-technology-work-all

Lagerlöf, N.-P. (2003). Gender Equality and Long-Run Growth. *Journal of Economic Growth*, 8(4), 403–426. JSTOR. http://www.jstor.org/stable/40215889

Larson, D. K., & Sung, C.-H. (2009). Comparing student performance: Online versus blended versus face-to-face. *Journal of Asynchronous Learning Networks*, 13(1), 31–42.

Learning Center I. (2021, July 10). [Personal communication].

Learning Center II. (2021, July 22). [Personal communication].

Lee, J. (2020). Statistics, Descriptive. In A. Kobayashi (Ed.), *International Encyclopedia of Human Geography* (Second Edition) (pp. 13–20). Elsevier. https://doi.org/10.1016/B978-0-08-102295-5.10428-7

Lewis, L. J. (1960). Education in a new nation: Ghana. *The Phi Delta Kappan*, 41(4), 155–158. JSTOR. http://www.jstor.org/stable/20342372

Lewis, W. A. (2003). *Theory of economic growth* (1st ed.). Routledge.

Li, M. (2012). Using the propensity score method to estimate causal effects: A review and practical guide. *Organizational Research Methods*, 1–39.

Lonska, J., & Mietule, I. (2015). The impact of human capital development on the economic and social development of a country: Empirical study. *Environment. Technology. Resources. Proceedings of the International Scientific and Practical Conference*, 2, 174. https://doi.org/10.17770/etr2015vol2.268

Lutza, W., Crespo Cuaresma, J., Kebede, E., Prskawetz, A., Sanderson, W. C., & Striessnig, E. (2019). Education rather than age structure brings demographic dividend. *Proceedings of the National Academy of Sciences*, 116(26), 12798–12803. https://doi.org/10.1073/pnas.1820362116

Luy, M., Zannella, M., Wegner-Siegmundt, C., Minagawa, Y., Lutz, W., & Caselli, G. (2019). The impact of increasing education levels on rising life expectancy: A decomposition analysis for Italy, Denmark, and the USA. *Genus*, 75(1), 11. https://doi.org/10.1186/s41118-019-0055-0

Makdisi, G. (1970). Madrasa and university in the Middle Ages. *Studia Islamica*, 32, 255. https://doi.org/10.2307/1595223

Mampane, Ruth M., Omidire, Margaret F., R. M., Aluko, Folake R., M. F., & Aluko, F. R. (2018). Decolonising higher education in Africa: Arriving at a glocal solution. South *African Journal of Education*, 38(4), 1–9. https://doi.org/10.15700/saje.v38n4a1636

Mariz-Perez, R. M., Teijeiro-Alvarez, M. M., & Garcìa-Alvarez, M. T. (2012). The relevance of human capital as a driver for innovation. *Cuadernos de Economía*, 35(98), 68–76. https://doi.org/10.1016/S0210-0266(12)70024-9

Marriam-Webster.com Dictionary. (2023). Human capital. In Marriam-Webster Dictionary. Marriam-Webster. https://www.merriam-webster.com/dictionary/human%20capital

Materu, P. (2007). *Higher education quality assurance in Sub-Saharan Africa: Status, challenges, opportunities and promising practices* (No. 124; World Bank Working Paper). The World Bank.

Mawere, M., & Stam, G. (2019). eLearning in an African place: How 'alien' eLearning models are failing many in Africa. In K. Rannenberg (Ed.), *International Conference on Social Implications of Computers in Developing Countries* (pp. 421–433). UNESCO.

MoE. (2017). *Education strategic plan 2018-2030*. Ministry of Education, Ghana.

Mohamedbhai, G. (2014). Massification in higher education institutions in Africa: Causes, consequences and responses. *Journal of African Higher Education*, 1.

Mohan, G. (2009). Structural adjustment. In R. Kitchin & N. Thrift (Eds.), *International Encyclopedia of Human Geography* (pp. 1–9). Elsevier. https://doi.org/10.1016/B978-008044910-4.00123-1

Moore, M. G. (Ed.). (2019). *Handbook of distance education* (Fourth edition). Routledge.

Morris, P. W. G., & Hough, G. H. (1987). *The anatomy of major projects: A study of the reality of project management*. John Wiley and Sons. http://inis.iaea.org/search/search.aspx?orig_q=RN:21028774

Mosweunyane, D. (2013). The African Educational Evolution: From Traditional training to formal education. *Higher Education Studies*, 3(4), p50. https://doi.org/10.5539/hes.v3n4p50

Muller, C., & de Vasconcelos Aguiar, J. P. (2022, March). Internet Society [Organization]. *What is the digital divide?* https://www.internetsociety.org/blog/2022/03/what-is-the-digital-divide/

Nampala, P., Kityo, R., Makuma-Massa, H., & Adipala, E. (2017). Tracing the evolution of higher education institutions and linkage to rural development in Africa. *African Journal of Rural Development*, 2(2), 143–151.

Nana Mbinkeu, R. C. (2013). Analysis and Design of Mobile Payment Platform in African Context. In K. Jonas, I. A. Rai, & M. Tchuente (Eds.), *E-Infrastructure and e-Services for Developing Countries* (pp. 143–152). Springer Berlin Heidelberg.

Ndofirepi, A., Mngomezulu, B., & Cross, M. (2017). Internationalization, regionalization and Africanization: A critical gaze. In J. Knight & E. T. Woldegiorgis (Eds.), *Regionalization of African Higher Education* (pp. 47–65). SensePublishers. https://doi.org/10.1007/978-94-6300-956-0_4

Nerozzi, S., & Nuti, P. (2011). Adam Smith on family. *History of Economic Ideas*, 19(2), 11–41. JSTOR. http://www.jstor.org/stable/23723536

Nguyen, T. (2015). The effectiveness of online learning: Beyond no significant difference and future horizons. *MERLOT Journal of Online Learning and Teaching*, 11(2), 11.

Noble, U. (2018). *Algorithms of oppression: How search engines reinforce racism*. NYU Press.

Norum, K. E. (2012). Artifacts. In L. M. Given (Ed.), *Methods*, The SAGE Encyclopedia of Qualitative Research. SAGE Publications, Inc.

OECD. (2018). Bridging the digital gender divide: Include, upskill, innovate (p. 151). *Organisation of Economic Co-operation and Development.*

Olatokun, W. (2008). Gender and national ICT policy in Africa: Issues, strategies, and policy options. *Information Development - INF DEV*, 24, 53–65. https://doi.org/10.1177/0266666907087697

Oliver, R. W. (1996). *International economic co-operation and the World Bank*. Macmillan.

Olmos, A., & Govindasamy, P. (2015). Propensity scores: A Practical introduction using R. *Journal of Multidisciplinary Evaluation*, 11(25), 68–88. https://journals.sfu.ca/jmde/index.php/jmde_1/article/view/431

Omar, S. M. (2012). Rethinking development from a Postcolonial perspective. *Journal of Conflictology*, 3(1), 42–49.

Ostry, J. D., Loungani, P., & Furceri, D. (2016, June). Neoliberalism: Oversold? *IMF Finance and Development*.

Ouma, C. (2021). Online learning perception among college students during COVID-19 pandemic around the world: Review. *African Educational Research Journal*, 9(3), 790–799.

Pack, H., & Nelson, R. R. (1999). The Asian miracle and modern growth theory. The World Bank. https://doi.org/10.1596/1813-9450-1881

Paschal, M. J., & Mkulu, D. G. (2020). Online classes during COVID-19 pandemic in higher learning institutions in Africa. *Global Research in Higher Education*, 3(3), p1. https://doi.org/10.22158/grhe.v3n3p1

Pearl, J. (2009). Causal inference in statistics: An overview. *Statistics Surveys*, 3. https://doi.org/10.1214/09-SS057

Perez, A. (2019). *Assessing quality in mixed methods research: A case study operationalizing the legitimation typology*. [Unpublished Dissertation]. University of Nebraska, Lincoln 109.

Peters, M. A. (2019). Ancient centers of higher learning: A bias in the comparative history of the university? *Educational Philosophy and Theor*y, 51(11), 1063–1072. https://doi.org/10.1080/00131857.2018.1553490

Peugh, J. L., & Enders, C. K. (2004). Missing data in educational research: A review of reporting Practices and suggestions for improvement. *Review of Educational Research*, 74(4), 525–556. https://doi.org/10.3102/00346543074004525

Pew Research Center. (2018a). A*t least a million Sub-Saharan Africans moved to Europe since 2010* (p. 24).

Pew Research Center. (2018b). *Internet connectivity seen as having positive impact on life in Sub-Saharan Africa*.

Polonenko, L. M., Besada, H., Tok, M. E., & Bada, A. (2019). Conceptual foundations of South-South Cooperation. In L. M. Polonenko, M. E. Tok, & H. G. Besada (Eds.), *Innovating South-South Cooperation* (pp. 1–28). University of Ottawa Press; JSTOR. https://doi.org/10.2307/j.ctvnp0kv2.7

Ponce, O. A., & Pagán-Maldonado, N. (2015). Mixed methods research in education: capturing the complexity of the profession. *International Journal of Educational Excellence*, 1(1), 111–135. https://doi.org/10.18562/IJEE.2015.0005

Powdthavee, N., Lekfuangfu, W. N., & Wooden, M. (2015). What's the good of education on our overall quality of life? A simultaneous equation model of education and life satisfaction for Australia. *Journal of Behavioral and Experimental Economics*, 54, 10–21. https://doi.org/10.1016/j.socec.2014.11.002

Priemus, H. (2007). Development and design of large infrastructure projects: Disregarded alternatives and issues of spatial planning. *Environment and Planning B: Planning and Design*, 34(4), 626–644. https://doi.org/10.1068/b32109

Psacharopoulos, G. (1994). Returns to investment in education: A global update. *World Development*, 22(9), 1325–1343. https://doi.org/10.1016/0305-750X(94)90007-8

R Documentation. (n.d.). *R: Nonparametric preprocessing for parametric causal inference*. https://search.r-project.org/CRAN/refmans/MatchIt/html/00Index.html

R Packages (2e). (n. d.). R-Pkgs. https://r-pkgs.org/

Rabler, S. (2020). *The Challenges of the demographic dividend for African countries: A gender perspective* (Policy Paper No. 4). Agence Française de Development.

Rainbow, P. (1991). *The Foucault reader: An introduction to Foucault's though*t. Penguin.

Ramphele, M. (2023, March 8). Reimagining: New humans, new society, new higher education. *University World News*. https://www.universityworldnews.com/post.php?story=20230308090744719&utm_source=newsletter&utm_medium=email&utm_campaign=GLNL0730

Ravitch, S. M., & Carl, N. M. (2016). *Qualitative research: Bridging the conceptual, theoretical, and methodological*. SAGE.

Renteria, E., Souto, G., Mejía-Guevara, I., & Patxot, C. (2016). The Effect of Education on the Demographic Dividend. *Population and Development Review*, 42(4), 651–671. https://doi.org/10.1111/padr.12017

Robinson, J. A., & Torvik, R. (2005). White elephants. *Journal of public economics*, 89, 197–210.

Rodney, W. (1972). *How Europe underdeveloped Africa*. Vol. Online. Bogle-L'Ouverture.

Rogers, A., Castree, N., & Kilchin, R. (2013). *Youth bulge*. In Oxford dictionary of human geography. Oxford University Press.

Romer, P. M. (1989). *Endogenous technological change* (NBER Working Paper Series, p. 45) [Working Paper]. National Bureau of Economic Research. https://www.nber.org/system/files/working_papers/w3210/w3210.pdf

Rosenbaum, P. R. (2010). Observational studies. In P. Peterson, E. Baker, & B. McGaw (Eds.), *International Encyclopedia of Education* (Third Edition) (Third Edition, pp. 354–359). Elsevier. https://doi.org/10.1016/B978-0-08-044894-7.01354-3

Rosenbaum, P. R., & Rubin, D. B. (n.d.). The central role of the propensity score in observational studies for causal effects. *Biometricka*, 70(1), 41-55. https://doi.org/10.2307/2335942

Rosenbaum, P. R., & Rubin, D. B. (1984). Reducing bias in observational studies using subclassification on the propensity score. *Journal of the American Statistical Association,* 79(387), 516–524. JSTOR. https://doi.org/10.2307/2288398

Rousseeuw, P. J., & Leroy, A. M. (2003). *Robust regression and outlier detection.* Wiley & Sons.

Rovai, A. P., & Baker, J. D. (2012). Gender differences in online learning. *Quarterly Review of Distance Education*, 6(1), 31–44. Academic Search Complete. https://search.ebscohost.com/login.aspx?direct=true&db=a9h&AN=16746922&site=eds-live

Rubin, D. B. (1976). Inference and Missing Data. *Biometrika*, 63(3), 581-591. https://doi.org/10.2307/2335739

Russell, T. L., IDECC., & Center (IDECC), I. D. E. C. (2001). *The no significant difference phenomenon: A comparative research annotated bibliography on technology for distance education, as Reported in 335 Research Reports, Summaries and Papers*. IDECC. https://books.google.com/books?id=W7Z_wgEACAAJ

Ruth, S. (2018). Faculty opposition to online learning: Challenges and opportunities. *International Journal of Technology in Teaching and Learning*, 14(1), 12–23.

Saint, W. S. (1992). *Universities in Africa: Strategies for stabilization and revitalization*. World Bank.

Salgado, F. P., & Rikers, J. (2017). International e-learning programmes for sustainable development in higher education in Europe and Africa. In G. Michelsen & P. J. Wells (Eds.), A *Decade of Progress on Education for Sustainable Development: Reflections from the UNESCO Chairs Programme* (pp. 48–58). UNESCO.

Samoff, J., & Carrol, B. (2003). *From manpower planning to the knowledge era: World Bank policies on higher education in Africa* (ED-2004/WS/8; UNESCO Forum Occasional, p. 98). UNESCO.

Samuels, B. (2013). *Being present. Inside Higher Education*. https://www.insidehighered.com/views/2013/01/24/essay-flaws-distance-education

Santos, B. (2014). *Epistemologies of the South: Justice against epistemicide.* Routledge.

Santos, B. (2016). Epistemologies of the South and the future. *From the European South*, 1, 17–29.

Santos Silva, M., & Klasen, S. (2021). Gender inequality as a barrier to economic growth: A review of the theoretical literature. *Review of Economics of the Household*, 19(3), 581–614. https://doi.org/10.1007/s11150-020-09535-6

Sawyerr, A. (2004). Challenges facing African universities: Selected issues. *African Studies Review*, 47(1), 1–59. https://doi.org/10.1017/S0002020600026986

Schoonenboom, J., & Johnson, R. B. (2017). How to construct a mixed methods research design. *KZfSS Kölner Zeitschrift Für Soziologie Und Sozialpsychologie*, 69(S2), 107–131. https://doi.org/10.1007/s11577-017-0454-1

Schultz, T. W. (1961). Investment in Human Capital. *The American Economic Review*, LI(1), 1–17.

Schultz, T. W. (1974). *Economics of the family: Marriage, children, and human capital.* University of Chicago Press.

Schwab, K. (2016, January 14). *The Fourth Industrial Revolution: What it means, how to respond*. World Economic Form. https://www.weforum.org/agenda/2016/01/the-fourth-industrial-revolution-what-it-means-and-how-to-respond/

Sen, A. (1999). *Development as freedom*. Anchor Books/Random House.

Shizha, E., & Makuvaza, N. (Eds.). (2017). *Re-thinking postcolonial education in Sub-Saharan Africa in the 21st century: Post-millennium development goals*. SensePublishers. https://doi.org/10.1007/978-94-6300-962-1

Simeon, A. N., Babtunde, A. A., Abiodun, N. L., Olu, R. O., & Emem, A. I. (2022). Uptake, barriers, and determinants of e-Learning among university students in selected low-income countries in Sub-Saharan Africa amidst the COVID-19 disruption: An online survey. *Advances in Medical Education and Practice*, 13, 609–617.

Sinah Theres Kloß. (2017). The Global South as subversive practice: Challenges and potentials of a Heuristic concept. *The Global South*, 11(2), 1–17. JSTOR. https://doi.org/10.2979/globalsouth.11.2.01

Smith, A. (1776). *An inquiry into the nature and causes of the wealth of nations*. W. Strahan and T. Cadell. https://www.globalgreyebooks.com/wealth-of-nations-ebook.html

Smith, A. (1863). *The theory of moral sentiments and on the origins of language.* Henry G. Bohn.

Stern, B. S. (2004). A Comparison of online and face-to-face instruction in an undergraduate Foundations of American Education Course. *Contemporary Issues in Technology and Teacher Education*, 4(2), 196–213.

Stiglitz, J. (2022, April 4). Shock therapy for neoliberals. *Project Syndicat*e.

Stiglitz, J. E. (2019, November 4). The end of Neoliberalism and the rebirth of history. P*roject Syndicate.*

Stratmon, D. L. (1959). The Ghana educational system. *The Journal of Negro Education*, 28(4), 394–404. JSTOR. https://doi.org/10.2307/2293596

Stuart, E. A. (2010). Matching methods for causal inference: *A Review and a Look Forward. Statistical Science,* 25(1). https://doi.org/10.1214/09-STS313

Submarine Networks. (n.d.). Submarine cables in Africa. *Submarine Networks.* https://www.submarinenetworks.com/en/africa

Suhail, N. A. (2008). Assessing implementation of blended learning in constrained low bandwidth environments. In *Special topics in computing and ICT research: Strengthening the role of ICT in developing countries*: Vol. Vol 1 (pp. 377–390). Fountain Publishers.

Sun, P.-C., Tsai, R. J., Finger, G., Chen, Y.-Y., & Yeh, D. (2008). What drives a successful e-Learning? An empirical investigation of the critical factors influencing learner satisfaction. *Computers & Education,* 50(4), 1183–1202. https://doi.org/10.1016/j.compedu.2006.11.007

Sweetland, S. R. (1996). Human Capital Theory: Foundations of a field of inquiry. *Review of Educational Research*, 66(3), 341–359. https://doi.org/10.3102/00346543066003341

Tafesse, S. (2008). The mathematical basis of the calendar used by the Ethiopian Orthodox Twahedo Church for fasting periods and religious holidays. *East African Journal of Sciences,* 2, 79–85.

Tagoe, M. (2012). Student's perception on incorporating e-learning into teaching and learning at the University of Ghana. *International Journal of Education and Development Using Information and Communication Technolog*y, 8(1), 91–103.

Tagoe, M. A. (2012). Sixty years of university-based education in Ghana: Challenges and prospects of making transition into a lifelong learning institution. *International Journal of Lifelong Education,* 31(2), 135–156. https://doi.org/10.1080/02601370.2012.663798

Tech experts Ghana. (2021, July 26). [Personal communication].

Teferra, D., & Altbach, P. G. (2003). *African higher education: An international reference handbook*. Indiana University Press. https://books.google.rw/books?id=RROdAAAAMAAJ

Teixeira, P. N. (2014). Gary Becker's early work on human capital – collaborations and distinctiveness. *IZA Journal of Labor Economics*, 3(1), 12. https://doi.org/10.1186/s40172-014-0012-2

The Economist. (2007, August 5). Gary Becker's concept of human capital. *The Economist*. https://www.economist.com/schools-brief/2017/08/05/gary-beckers-concept-of-human-capital

The Economist. (2015, March 2). Why does Kenya lead the world in mobile money? *The Economist*. https://www.economist.com/the-economist-explains/2015/03/02/why-does-kenya-lead-the-world-in-mobile-money

The World Bank. (2016). *Digital dividends: World development report 2016* (World Development Report, p. 359). The World Bank. https://www.worldbank.org/en/publication/wdr2016

The World Bank. (2020). Metadata glossary. https://databank.worldbank.org/metadataglossary/all/series

The World Bank. (2023). *Human Capital Projec*t. The World Bank Group. https://www.worldbank.org/en/publication/human-capital

Thorsen, D. E., & Lie, A. (2007). *What is neoliberalism?*

Tipton, E. (2013). Improving generalizations from experiments using propensity score subclassification: Assumptions, properties, and contexts. *Journal of Educational and Behavioral Statistics*, 38(3), 239–266. JSTOR. http://www.jstor.org/stable/41999424

Trines, S. (2018). Educating the masses: The rise of online education in Sub-Saharan Africa and South Asia. *World Education News + Reviews*.

Trucano, M. (2015, September 8). World Bank Blogs [World Bank]. Surveying ICT Use in Education in Africa. https://blogs.worldbank.org/edutech/surveying-ict-use-education-africa

Tulinayo, F. P., Ssentume, P., & Najjuma, R. (2018). Digital technologies in resource constrained higher institutions of learning: A study on students' acceptance and usability. *International Journal of Educational Technology in Higher Education*, 15(1), 36. https://doi.org/10.1186/s41239-018-0117-y

Turan, Z., Kucuk, S., & Cilligol Karabey, S. (2022). The university students' self-regulated effort, flexibility and satisfaction in distance education. *International Journal of Educational Technology in Higher Education*, 19(1), 35. https://doi.org/10.1186/s41239-022-00342-w

Tyers-Chowdhury, A., & Binder, G. (2021). *What we know about the gender digital divide for girls: A literature review* [Evidence Brief]. UNICEF. https://www.unicef.org/eap/media/8311/file/What%20we%20know%20about%20the%20gender%20digital%20divide%20for%20girls:%20A%20literature%20review.pdf

UG. (2014). UG Enrollment. Student Enrollment Statistics: 2013/14. https://www.ug.edu.gh/irpo/sites/irpo/files/Enrolment%202014.pdf

UGLC Focus Group. (2021, August 3). [Personal communication].

UN, D. (2023). Gross enrolment ratio: Tertiary education [Database]. http://data.un.org/Default.aspx

UNECA. (1997). *Non-formal and distance education in Ethiopia lessons and experiences* [Technical paper]. https://repository.uneca.org/handle/10855/14901

UNESCO. (2019). *Connecting Africa through broadband: A strategy for doubling connectivity by 2021 and reaching universal access by 2030* (p. 140) [Report]. https://www.broadbandcommission.org/Documents/working-groups/DigitalMoonshotforAfrica_Report.pdf

UNESCO. (2022). Global employment trends for Youth 2022 (p. 300). UNESCO. https://www.ilo.org/global/publications/books/WCMS_853321/lang--en/index.htm

UNESCO. (2023a). *Education in Africa*. UNESCO. https://uis.unesco.org/en/topic/education-africa

UNESCO IIEP. (2022). *Assessing qualification mismatch in sub-Saharan Africa: Concepts, indicators, and data sources*. UNESCO.

UNESCO, U. (2023b). The UNESCO Institute for Statistics [Database]. http://data.uis.unesco.org/#

United Nations. (2017). *World population prospects: The 2017 revision*. United Nations Department of Economic and Social Affairs. https://population.un.org/wpp/Publications/Files/WPP2017_KeyFindings.pdf

University of Ghana. (2014). ICT based distance education project (Chinese phase 2 ICT project). University of Ghana.

University of Ghana: AE/HRS. (2022). Department of Adult Education and Human Resource Studies :Brief History of the Department. https://scde.ug.edu.gh/department/department-adult-education-and-human-resource-studies

University of Ghana/DDE. (2022). [Department History]. Department of Distance Education. https://www.ug.edu.gh/distance/

USAID. (2019). *United States Agency for International Development History* [Organization]. USAID. https://www.usaid.gov/who-we-are/usaid-history

V. V. Bhanoji Rao. (1999). East Asian economies: Trends in poverty and income inequality. *Economic and Political Weekly*, 34(18), 1029–1039. JSTOR. http://www.jstor.org/stable/4407905

Vuolo, M., Uggen, C., & Lageson, S. (2018). To match or not to match? Statistical and substantive considerations in audit sesign and analysis. In S. M. Gaddis (Ed.), *Audit*

Studies: Behind the Scenes with Theory, Method, and Nuance (pp. 119–140). Springer International Publishing. https://doi.org/10.1007/978-3-319-71153-9_6

Walters, B. B., Rönnbäck, P., Kovacs, J. M., Crona, B. I., Hussain, S. A., Badola, R., Primavera, J. H., Barbier, E. B., & Dahdouh-Guebas, F. (2008). Ethnobiology, socio-economics and management of mangrove forests: A review. *Aquatic Botany*, 89, 220–236.

Weale, M. (1993). A critical evaluation of rate of return analysis. *The Economic Journal*, 103(418), 729–737. JSTOR. https://doi.org/10.2307/2234545

Willis, P. (2004). Twenty-five years on: Old books, new times. In N. Dolby & G. Dimitriadis (Eds.), *Learning to Labor in a New Times* (pp. 167–196). Routledge Falmer.

Wolf, M. (2014). Shaping globalization. *Finance & Development*, 51(3), 22–25.

World Bank DataBank. (2023). [Database]. World Bank. https://databank.worldbank.org

World Economic Forum. (2022). *Global gender gap report 2022* (Insight Report No. 2022; p. 374). World Economic Forum. https://www3.weforum.org/docs/WEF_GGGR_2022.pdf

Xie, Y. (2011). Causal inference and heterogeneity bias in social science. *Information, Knowledge, Systems Management*, 10(1), 279–289. https://doi.org/10.3233/IKS-2012-0197

Yayboke, E. (2020, April 10). The need for a leapfrog strategy [Organization blog]. Center for Strategic & International Studies. https://www.csis.org/analysis/need-leapfrog-strategy

Yin, R. (2009). *Case study research: Design and methods.* Sage Publications.

Yu, Z., & Deng, X. (2022). A meta-analysis of gender differences in e-Learners' self-efficacy, satisfaction, motivation, attitude, and performance across the world. *Frontiers in Psychology*, 13.

Zenawi, M. (2011). States and markets: Neoliberal limitations and the case for a developmental dtate. In A. Noman, K. Botchwey, H. Stein, & J. E. Stiglitz (Eds.), *Good Growth and Governance in Africa: Rethinking Development Strategies*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199698561.003.0005

Zvobgo, K., & Loken, M. (2020). Why race matters in international relations. *Foreign Policy*, 1–10.