UNIVERSITY OF CALIFORNIA

Santa Barbara

The Cycle of Bias: Skin Tone Biases in Algorithms and the Implications for Technology Diffusion

A Thesis submitted in partial satisfaction of the

requirements for the degree Master of Arts

in Communication

by

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December 2023

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October 2023

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Abstract

This research seeks to understand how skin tone bias in image recognition algorithms impacts users' adoption and usage of image recognition technology. We employed a diffusion of innovations framework to explore perceptions of compatibility, complexity, observability, relative advantage, trialability, and reinvention to determine their influence on participants' utilization of image recognition algorithms. Despite having more susceptibility to algorithmic bias, individuals with darker skin tones perceived these algorithms as having greater levels of compatibility and relative advantage, being more observable, and less complex and thus used them more extensively compared to those with lighter skin tones. Individuals with darker skin tones also displayed higher levels of reinvention behaviors, suggesting a potential adaptive response to counteract algorithmic biases.

Keywords: algorithm bias, artificial intelligence, diffusion of innovations, technology use, digital divide

Algorithms play a pivotal role in shaping the daily lives of individuals in digitally connected societies. From healthcare (Rajkomar et al., 2018), hiring (Kuncel et al., 2013) and parole sentencing (Laqueur & Copus, 2022) to social media feeds, dating apps (Rosenfeld et al., 2019), and search engines (Google Search Central, 2023), algorithms are increasingly created with the goal of making our lives safer and easier. For example, smartwatches, which use image sensing technology to detect physiological data such as heartrate, increasingly have been praised for their potential to provide valuable data to healthcare providers (Massoomi & Handberg, 2019), and have been credited with saving lives (Epstein, 2021). However, algorithms do not benefit everyone equally. For example, multiple smartwatches have been found to provide less accurate data to those with dark skin (Ajmal et al., 2021; Ray et al., 2021). This is an instance of algorithm bias—where a device using an algorithm advantages certain groups of users or data over others.

Algorithm bias is a widely recognized problem. Research shows that biased healthcare algorithms have been shown to prioritize White patients over Black patients (Obermeyer et al., 2019); facial recognition algorithms are more likely to misgender dark-skinned individuals (Zou & Schiebinger, 2018); search engines perpetuate racial and ethnic stereotypes (Noble, 2018: Sweeny, 2013); certain optically-activated water dispensers do not work for dark skin tones (Ren & Heacock, 2022); risk assessment algorithms have wrongfully identified children as potential maltreatment victims (De-Arteaga et al., 2020); and algorithms have wrongfully label women as more likely to re-offend when determining parole eligibility (Hamilton, 2019). Although there has been a recent focus developing algorithms unafflicted by such bias (Azoulay, 2018; U.S. EEOC, 2022), the importance of understanding the downstream effects of how humans detect and respond to such bias in algorithms has largely been neglected. Previous research concerning how people think about the downstream effects of algorithms has been sparse and largely qualitative, focusing on folk theories of how people think about algorithms *generally* (DeVito et al., 2018; Rabassa, 2022; Ytre-Arne & Moe, 2021), ignoring bias *specifically*. Instead, it would be useful to understand how users respond to systematic biases.

In particular, discerning how skin tone bias may affect user behavior is pivotal, not merely for fostering technological awareness and equity but also for revealing its broader societal implications. An individual's perceptions of technology, shaped by their experiences with algorithmic biases, may significantly impact their willingness to adopt and integrate similar technology into their daily lives. Furthermore, these biases may impact *how* individuals use similar technologies. This study asks: how does algorithm bias influence the diffusion and use of image recognition technology? We frame this research question within the diffusion of innovations and digital divide theories, offering a lens to understand the ramifications of algorithmic bias on individual technology adoption in the contemporary digital era.

We begin answering the how algorithm bias may affect user adoption behavior by outlining the various ways algorithms can exhibit bias. Then, we hone in on image recognition algorithms, a common type of algorithm that tends to systematically advantage certain users over others, in ways that are not intended as a function of the algorithm. Image recognition algorithms provide an ideal context to begin exploring the impacts of algorithm bias as they (1) have been widely shown to exhibit bias and (2) are used by individuals across various contexts.

Literature Review

Algorithms, at their most basic level, are instructions for solving a problem or task (Pew Research Center, 2017). Instructions for putting together furniture and recipes for cooking are algorithms. Computer code is also algorithmic. Programmers create code that gives a computer a set of instructions for how to accomplish a task (e.g., what search results to display first when making a web query). Artificial Intelligence (AI) is made of algorithms with the goal of reproducing specific kinds of intelligence, such as language processing, human learning, and planning. This is accomplished through a variety of ways, such as employing statistical models and utilizing machine learning (ML; i.e., employing combinations of algorithms and data to mimic intelligence). For the purpose of this paper the term ***algorithm(s)*** will refer to *the computer code containing a set of instructions that are employed to make a particular technology work*; this includes AI algorithms. Because algorithms are merely instructions created by humans—or in the case of AI, algorithmic systems that are overseen by humans —they are prone to reflecting their creators, including the bias (intentional or not) of those creators. Danks and London (2017) define algorithm bias as "an algorithm that deviates from some standard"; we have chosen to expand on this definition, defining ***algorithm bias*** as *an algorithm that deviates from some standard in a manner that systematically dis/advantages a category of users or a category of data over another, in ways that are not intentionally designed as a function of that algorithm.* For example, some smartwatches would be considered biased because they do not complete their intended purpose of giving everyone, regardless of skin tone, accurate physiological data.

Why Does Algorithm Bias Occur?

Danks and London (2017) note several ways bias may occur. First, <u>training data bias</u> occurs when an algorithm is trained on data that is not generalizable to the intended purpose of that algorithm. For instance, if a facial recognition algorithm primarily learns from a dataset dominated by lighter faces, it might underperform when identifying a broader spectrum of skin tones. Klare et al. (2012) demonstrated that commercially available facial recognition systems reported consistently lower matching accuracy when assessing photos of Black individuals than White individuals. When the researchers intentionally trained their algorithm using exclusively Black faces, the algorithm's matching accuracy significantly improved.

When an algorithm is used outside of its intended context, this is known as <u>transfer context bias</u>. There are many instances when it may be desirable to apply an algorithm to a new context. However, biases can arise when the new context is substantively different from the intended context of the algorithm. For example, a facial recognition program created for unlocking and locking personal phones may not employ the precise measures required in a highly consequential context such as facial recognition for law enforcement or financial purposes, despite the similarity in function.

Finally, <u>interpretation bias</u> occurs when the output of an algorithm is misunderstood by the user of the algorithm. There may be many instances when it is desirable to use an algorithm, but without proper training of the end user, interpretation bias can occur. For example, imagine a facial recognition algorithm used for airport security screening that gives each passenger a score between 0 and 100 indicating the percentage of similarity their face shares with a criminal on a watchlist. A security officer who is not properly trained on the algorithm may interpret a score of 80 as the algorithm being 80% sure that the passenger is one of the criminals on the watchlist, when in fact the score indicates that they have similar faces.

Because algorithm bias arises from a multitude of factors, often reflecting human bias in both intentional and unintentional ways, it is unlikely that algorithm bias will be fully resolved in the near (or distant) future. Furthermore, as new technologies emerge, so too will new instances and contexts of algorithm bias. Consequently, to better understand the potential consequences that algorithm bias can have on technology users, we turn our attention to a specific application, image recognition algorithms.

Image Recognition Algorithms

Image recognition algorithms are the underlying technology used to automatically identify images based on their color, texture, shape, and special relationship features (Zhang et al., 2020). Examples of image recognition algorithms include automatic social media taggers, facial recognition algorithms, the algorithms used by smartwatches to detect physiology, and algorithms used to detect hands for soap dispensers or hand dryers. Notwithstanding their general proficiency to help users with their daily tasks, these algorithms often display a significant flaw—a consistent bias towards lighter skin tones (Ajmal et al., 2021; Buolamwini & Gebru, 2018; Grother et al., 2019; Klare et al. 2012; Ray et al., 2021; Ren & Heacock, 2022; Zou & Schiebinger). To illustrate this, consider the findings on facial recognition tools developed by companies such as IBM, whose facial recognition algorithm was found to have a 34.7 % error rate for dark skinned females but performed with an error rate of only 0.3% for light skinned males (Buolamwini & Gebru, 2018). Similarly, while smartwatches serve as health aids, their precision wanes for darker-skinned individuals (Ajmal et al., 2021). More disconcerting is the performance of emerging autonomous vehicles, with certain models detecting darker-skinned individuals with a 10% lower accuracy than lighter-skinned ones (Wilson et al., 2019).

A particularly striking illustration is provided by a 2019 study conducted by the United States National Institute of Standards and Technology (NIST) (Grother et al., 2019). In their assessment, NIST evaluated 189 facial recognition algorithms from 99 commercial developers, using a sample of 18.27 million images. Their objective was to ascertain the extent and nature of demographic differences in the performance of these algorithms. The results revealed demographic disparities in the majority of tested algorithms. Notably, these algorithms demonstrated higher bias for West and East African, as well as East Asian individuals (with the exception of algorithms developed in China). In contrast, Eastern Europeans recorded the lowest bias. Essentially, these findings underscore the prevalence of demographic biases in image recognition algorithms. A final remark regarding the NIST report—the top-performing algorithms showed limited bias, and the nature of this bias often varied based on the algorithm's developer, with Chinese-produced algorithms accurately identifying East Asian faces, for instance. This suggests that the biases observed are not due to technological limitations, such as lighting, resolution, pattern recognition, etc.

Before delving into the potential impact of skin tone bias on perceptions and the use of technology, it is important to discuss our emphasis on skin tone bias, distinguishing it from racial and ethnic biases. Although racial and ethnic group membership is commonly used to evaluate and critique algorithms (Nobel, 2018; Obermeyer et al., 2019; Zhang, 2015; Zou & Schiebinger, 2018) and may be a justifiable measure for certain text-based algorithms that are unable to assess phenotypical information (e.g., search engines), racial and ethnic group membership falls short in its usefulness for assessing image recognition algorithms. Image recognition algorithms detect a user's physical features and phenotypic features can vary widely within racial and ethnic groups; therefore, individuals who belong to the same racial/ethnic group may have vastly different skin tones leading to markedly different interactions with image recognition technologies. Therefore, skin tone, not race or ethnicity, is examined to assess the implications of bias in image recognition algorithms. As discussed by Buolamwini and Gebru (2018), this may be one of the most accurate ways to assess bias in image recognition algorithms as skin tone (1) provides a more visually precise way to measure inconsistent effectiveness privileging certain users and (2) allows the research done on image recognition algorithms to be generalizable across racial and ethnic group memberships.

As discussed above, image recognition algorithms are known to exhibit bias against darker skin tones. It is insufficient to recognize this bias without delving into its broader implications. In this case, we examine the influence of skin tone on the adoption and use of image recognition technologies. On one hand, if image recognition algorithms consistently underperform for a group of users it may impact technology *adoption* within that group of similar technologies, possibly sidelining individuals with dark skin tones from benefits experienced by light skin. For example, some groups could choose not to adopt technology utilizing facial recognition that facilitates social connections (e.g., choosing not to use social media tags) because of their propensity to misidentify those with darker skin tones [Barocas, S., & Selbst, 2016; Zhang 2015b]. On the other hand, users may change *how* they use technology in order to counteract the adverse impacts stemming from bias. For example, they may alter how they use a particular technology, with possible implications such as increasing privacy and security risks (e.g., using a PIN instead of biometric security on phones). Although some algorithms may have a viable replacement that mitigates the potential harm of different adoption and use patterns, or may be perceived as more adaptable to individual needs, other algorithms might lack such alternatives or not be viewed as flexible. Ren and Heacock (2022) found that the darker the skin that was presented to an automatic water faucet sensor, the longer it took to dispense water, with the darkest skin tone failing to activate the sensor most of the time. These deficiencies, in environments with no convenient alternatives, may have predictable effects on use that have the potential to increase disparities and health risks between groups.

A Digital Divide Perspective

One way to contextualize these disparities is through the lens of the digital divide, which addresses how inequalities related to technological access (first-level), skills (second-level), and functionality and usage activities (third-level) affect social, economic, political, and other disparities (Lythreatis et al., 2022). If these divides are unchecked, they can create and exacerbate disparities between groups. This is known as the Matthew effect. First proposed by Robert K. Merton in 1968, the Matthew effect (paraphrasing the Biblical passage Matthew 13:12) is a phenomenon where “the rich get richer and the poor get poorer.” In other words, those who are already advantaged become relatively more so, whereas those who are systematically marginalized become relatively more so, even if they adopt and use the innovation and gain some benefits.

The digital divide can exacerbate the Matthew effect, as having digital skills and working technology can be a key factor in determining a group’s ability to benefit from technology and access critical resources. For example, if a bank decides to adopt (unbeknownst to them) a biased facial recognition system as a secure and easy way for clients to access their accounts. In that case those clients for whom the facial recognition system works better for may be more likely to check their accounts and stay up to date on payments. However, the clients for whom the facial recognition system does not work well do not reap these benefits.

This narrative's significance extends beyond the immediate context, bringing us to one major concern with algorithm bias; past encounters with biased technology can shape future interactions with that technology, or even similar technologies. A bank client, previously disadvantaged by a biased banking system, may lack the confidence or skill to adopt similar, unbiased technologies in the future. This hesitation underscores the concept of *innovation negativism*, as posited by Rogers (2003), wherein prior negative adoption experiences shape future technology use. To examine the relationship between algorithm bias and adoption, we now turn to diffusion of innovations theory to examine the mechanisms through which algorithm bias may influence technology adoption.

Diffusion of Innovations Theory

Diffusion of innovations (DOI) theory explains how innovations (i.e., ideas, behaviors, or objects) are adopted, rejected, reinvented, or discontinued by a population (Rogers, 2003). According to DOI theory, an innovation can consist of hardware and/or software, products, processes, and services (Rogers, 2003). Hardware and software can diffuse throughout a population at different rates. Rogers (2003) used computer programs as an illustration of software, defining them as the combination of coded commands, instructions, and other informational components of a tool that facilitate specific tasks. Because algorithms (which are made up of code) are not physically tangible, they are necessarily limited to the software category. This is important, as technology that employs different algorithms (e.g., apps) will often diffuse at different rates than the piece of hardware (e.g., a phone) that hosts the apps. Even when a piece of hardware comes with software pre-installed, this does not necessarily mean that the software will be used, or that it will be updated at the same time as the hardware, or that the hardware will be appropriately updated to match the capabilities of updated software. For example, although a phone may come with pre-installed biometric security features such as facial recognition, the user may choose to use a PIN instead. In this case, even though the innovation of the phone diffused (hardware), the innovation of biometric security (software) did not.

The DOI framework maps how perceptions of image recognition algorithms affect the use and adoption of image recognition algorithms. Inherently, a biased algorithm will exhibit varied functionality across users from different groups. Such performance disparities between groups may subsequently influence group members perceptions of the algorithm and similar other algorithms (innovation negativism). DOI theory presents five primary perceptual innovation characteristics that influence adoption: (1) relative advantage (perceived advantage over other options), (2) complexity (perceived ease of understanding and use), (3) observability (seeing the innovation being used), (4) trialability (ability to test on a limited bases), and (5) compatibility (consistency with existing values, needs and experiences) (Rogers, 2003). Innovation negativism has the potential to impact perceptions across all five DOI characteristics, as will be discussed later.

Group membership also impacts how technology diffuses (Finney et al., 2004; Nehme et al., 2016). This may be because different groups have different experiences and values that affect the perceived relative advantage, complexity, observability, trialability and compatibility of an innovation, but also different resources and needs. For example, consider two individuals —one with light skin and one with dark skin—who are considering switching from using a PIN to facial recognition when unlocking their phone. When the individual with light skin attempts to use facial recognition to unlock their phone, they perceive it as faster and more convenient than using a PIN (higher relative advantage). However, because of bias in the facial recognition algorithm, it may function successfully only some of the time for darker skinned users, resulting in lower perceived relative advantage, and potentially decreasing adoption of the facial recognition feature. In other words, skin tone can play a role in shaping experiences and perceptions of a new technology, affecting its perceived relative advantage and ultimately its diffusion among different groups.

Reinvention is a concept in DOI that refers to the degree to which the use of an innovation departs from how the innovation is intended to be used (Rogers, 2003). Innovations that can be reinvented are more likely to diffuse (Rogers, 2003). In cases of algorithm bias, when a technology user notices bias is present, they may engage in reinvention, finding workarounds for the bias instead of not adopting the technology altogether. For example, if an individual were to encounter a water dispenser that did not operate for them despite observing its functionality for users with a lighter skin tone, they may engage in reinvention by placing a lighter object (e.g., a paper towel) under the water dispenser to get it to work. Reinvention may act as a buffer against algorithm bias, enabling affected individuals to devise alternative use strategies when engaging with biased algorithms, thus eliminating the effect of bias on their adoption of image recognition algorithms.

Present Investigation

We adapted DOI measures to assess innovation characteristics with respect to four types of image recognition algorithms: phone unlocking facial recognition algorithms, facial recognition algorithms used to access financial systems such as bank accounts, social media facial filters, and image sensors like automatic water faucets. We selected these algorithms based on two primary criteria: they all utilize image recognition algorithms, and they encompass the two distinct types of image recognition algorithms with which individuals might interact, specifically facial recognition (used in phone unlock features, financial systems, and social media filters) and image sensors. Facial recognition technologies are image recognition algorithms that identify a person's face by identifying or measuring a person's facial features in an image (AWS, 2023), whereas image sensors are image sensing algorithms that convert an optical image into an electronic signal (Federal Agencies Digitization Guidelines Initiative, n.d.).

We seek to understand whether skin tone influences the degree to which users perceive image recognition algorithms' relative advantage, compatibility, complexity, observability, or trialability compared to other innovations; and whether perceptions across the five DOI characteristics determine an individual's tendency to use image recognition technology. We also seek to understand the moderating role that reinvention may play on the effect of skin tone on the tendency to use image recognition technology. Users who are more likely to reinvent may be able to overcome the barriers to technology use due to algorithm bias that some individuals experience. The ensuing section discusses the conceptual and operational definitions of the five DOI characteristics and reinvention in the context of this study. We propose several hypotheses to guide our investigation of how algorithm bias influences the diffusion and use of image recognition technology.

Relative advantage. Relative advantage is the degree to which an innovation is perceived as better than preceding innovations (Rogers, 2003). Relative advantage is grounded in perception rather than objective superiority and can be quantified in various ways: economic cost, decreased discomfort, social prestige, saving time and effort, and the immediacy of a reward (Rogers, 2003). In technology applications, relative advantage has been shown to be positively related to the perceived usefulness of a technology (Min et al., 2019) as well as the decision to adopt a technology (Vagnani et al., 2019). Algorithmic bias may decrease the perceived benefits of the algorithm by compromising its functionality for some users. For example, an image recognition algorithm such as an automatic facial recognition feature used to tag friends in a social media app, like the feature previously used by Facebook, may intend to have higher relative advantage than the alternative of tagging all a user's friends manually (saving time and effort). However, if the facial recognition feature only works for certain skin tones, the relative advantages diminish. Given the documented bias in algorithms based on the skin tone of the user, the following hypothesis is proposed:

H1: The effect of skin tone on the use of image recognition algorithms will be mediated by perceived relative advantage, such that those with lighter skin tones will perceive more relative advantage than those with darker skin increasing use of image recognition algorithms among users with lighter skin tones.

Should individuals with darker skin tones perceive image recognition algorithms as having less relative advantage compared to their counterparts with lighter skin tones, it would suggest that algorithm bias affects the perceived benefits of using a particular technology. Conversely, if those with darker skin tones find image recognition more advantageous than those with lighter skin tones, it could imply that individuals with darker skin tones have developed workarounds to algorithm bias (as discussed more in H5), making image recognition algorithms more desirable compared to earlier innovations.

Compatibility. Compatibility is the degree to which an innovation is consistent with past experiences, beliefs, and values (Rogers, 2003). Compatibility of an innovation hinges on (1) its alignment with the adoptee's sociocultural values and beliefs, (2) its congruence with previously introduced ideas, and (3) the adopter's need for the innovation (Rogers, 2003). Compatibility is positively related to the perceived usefulness of a technology (Min et al., 2019) as well as technology adoption (Rogers, 2003; Vagnani et al., 2019). As previously mentioned, a key determinant of compatibility is an individual's existing way of doing things. When an algorithm exhibits bias (for the adoptee or the adoptee's peers), it may hinder the seamless integration of the technology into one's life, thus decreasing perceptions of compatibility. Consider a facial recognition algorithm used to unlock a phone. If, due to inherent biases, the algorithm struggles to recognize people with darker skin tones, then the algorithm will disrupt the seamless integration of the facial recognition feature into the user's daily routine. While the technology's relative advantage might allow quicker access without manual password input, its compatibility is compromised because it fails to consistently integrate into the daily routines of all users. Furthermore, due to the bias in image recognition algorithms that causes them to exhibit poorer performance for individuals with darker skin tones (Buolamwini & Gebru, 2018; Ren & Heacock, 2022; Zhang, 2015; Zou & Schiebinger, 2018), even if the bias is removed, there is a possibility that those with darker skin tones may experience *innovation negativism,* using future image recognition algorithms less. For example, although the inaccurate and biased results associated with image sorting algorithms like those used by Google photos (Zhang, 2015) have purportedly been resolved (Barr, 2015), users who experienced algorithm bias in the previous version of the algorithm may choose not to use the updated version. Accordingly, the following is proposed:

H2: The effect of skin tone on the use of image recognition algorithms will be mediated by perceived compatibility, such that those with lighter skin tones will perceive more compatibility than those with darker skin tones, increasing use of image recognition algorithms among users with lighter skin tones.

If individuals with darker skin tones, due to algorithmic biases, perceive these image recognition algorithms as less compatible, it implies more than just reduced usage. It could signify a broader mistrust in the technology or a reliance on alternative solutions (*innovation negativism*). However, if these individuals find image recognition more compatible despite biases, it raises an intriguing possibility that faced with challenges, these users are innovating in ways to make the technology more relevant and beneficial in their daily lives.

Complexity. Complexity is the degree to which an innovation is perceived as hard to use and understand; innovations high in complexity will defuse more slowly throughout a population than those that are low in complexity (Rogers, 2003). In technology applications, complexity has been shown to be negatively related to perceived usefulness (Min et al., 2019), as well as to the decision to adopt a technology (Vagnani et al., 2019). The potential influence of algorithmic bias on the perception of complexity stems from its negative impact on the functional efficacy of image recognition algorithms, which in turn could give rise to the perception that image recognition algorithms are more difficult to use. A pre-existing bias in algorithms that causes them to advantage those with lighter skin tones over those with darker skin tones may impact perceptions of complexity in several ways. For example, a biased facial recognition algorithm may not immediately identify a user with darker skin, thus necessitating experimentation with the angle and lighting of the image to get the algorithm to function properly, adding an extra layer of complexity to the adoption process.

The same algorithm may also require multiple attempts before the user's face is recognized successfully, increasing the perceived difficulty in using the technology. Finally, if a biased image recognition algorithm sometimes does work as intended, but sometimes requires extra experimentation, this uncertainty may contribute to the algorithm seeming difficult to operate and thus more complex. Therefore, the following is proposed:

H3: The effect of skin tone on the use of image recognition algorithms is mediated by perceived complexity, such that those with lighter skin tones will perceive less complexity than those with darker skin tones, increasing use of image recognition algorithms among users with lighter skin tones.

Should individuals with darker skin tones perceive image recognition algorithms as more complex than those with lighter skin tones, it would point toward algorithmic bias as a factor that complicates their user experience. Conversely, if these individuals find image recognition algorithms less complex than those with lighter skin tones do, it could suggest that algorithmic biases compel them to engage in more troubleshooting, leading to increased familiarity with the algorithm.

Observability. Observability is the degree to which the benefits of an innovation are observable to others (Rogers, 2003). Observability is positively related to the perceived usefulness of a technology (Min et al., 2019). According to DOI, software-based technologies are not as easy to observe as hardware. For example, it may be easier to observe the benefits of using a phone, but more difficult to observe the benefits of biometric security on that phone. The theory of social proof states that individuals are influenced by the actions of those around them (Cialdini, 2007), especially those that they find to be similar in some way to themselves (Cialdini, 2007), or their group (Biagas & Bianchi, 2016). Since image recognition algorithms tend to perform more consistently and effectively for users with lighter skin tones than with darker skin tones, individuals with darker skin may not witness as frequently those with similar skin tones experiencing the advantages of image recognition algorithms. Therefore, the following is proposed:

H4: The effect of skin tone on the use of image recognition algorithms will be mediated by perceived observability, such that those with lighter skin tones will perceive more observability than those with darker skin tones, increasing use of image recognition algorithms among users with lighter skin tones.

If individuals with darker skin tones perceive image recognition as less observable, it could suggest algorithmic bias affecting the adoption of image recognition among individuals with similar skin tones, compared to those with lighter skin. Conversely, perceiving image recognition as more observable may indicate greater adoption of this technology among individuals with darker skin tones. If no differences exist in perceived observability between lighter and darker skin tones, it may result from the inherent opacity of software systems.

Trialability. Trialability refers to the ability to experiment with an innovation before adoption; innovations that are triable are more likely to be adopted (Rogers, 2003). For example, if someone can try to use biometric security on their phone before committing to using it all the time, it will be more likely to be adopted. The reasoning behind this lies in the capacity of preliminary testing to alleviate uncertainties, mitigate perceived risks, and lower costs associated with adopting the new technology (Rogers, 2003). Given the well-documented biases that favor lighter-skinned users in terms of technology efficiency and functionality, there could be existing skepticism, perhaps stemming from prior negative experiences with innovations (*innovation negativism*), which might deter darker-skinned users from sampling new technologies. However, if this relationship exists has yet to be seen. Therefore, we seek to examine the relationship between perception of skin tone bias in algorithms and trialability. Trialability may be affected by skin tone bias since pre-existing notions of bias may deter individuals from trying a technology. Given a lack of knowledge regarding the implications of algorithm bias on trialability the following research question is posited:

RQ1: Are perceptions of skin tone bias in image recognition algorithms associated with trialability?

Should perceptions of skin tone bias in image recognition algorithms be negatively associated with trialability, it would indicate that actively perceiving bias in algorithms decreases the likelihood of trying technology, which may in turn impact if people use to adopt that technology.

Reinvention. Reinvention is the “degree to which an innovation is changed or modified by a user in the process of adoption or implementation” (Rogers, 2003, p. 180). Because many image recognition algorithms privilege those with light skin (Buolamwini & Gebru, 2018; Ren & Heacock, 2022), people with lighter skin tones may not need to engage in reinvention behaviors as often as those with dark skin, such as (a) modifying the innovation (b) combining the innovation with other technologies or (c) redefining the innovation (reinterpret the purpose of an innovation). Take for example the case of the automatic water dispenser (Ren & Heacock, 2022). Those with lighter skin tones likely have no need to modify the invention to function for them because it already does. In this study, reinvention is conceptualized as (a) the frequency at which individuals tinker with or adjust existing image recognition systems to meet their needs, and (b) how often they use image recognition technology in ways that were not initially intended for the technology. Therefore, we propose:

H5. Those with lighter skin tones will engage in reinvention of technology using image recognition algorithms less often than those with dark skin tones.

If people with darker skin tones do engage in reinvention, it may mitigate some of the negative effects of algorithm bias as they are still able to reap the benefits of a technology while minimizing the drawbacks created by algorithm bias. On the other hand, if users with darker skin do not engage in reinvention they can either (1) use the technology as designed, despite the deficiencies or (2) choose not to adopt the technology. If they use the technology as conceived to be used, they may not receive the same benefits as those for whom the technology functions as intended. If they choose not to adopt the technology, they will forfeit all benefits (and disadvantages) that the technology provides.

Algorithm Knowledge

We make an assumption that an individual’s choice not to engage with certain image recognition technologies is due to the conscious or unconscious detection of algorithmic bias. However, we do not measure actual algorithm bias in our study, and therefore we cannot be sure that the effect of skin tone on the use of image recognition algorithms is determined by algorithm bias. One reason that we assume differences in image recognition technology use are due to algorithm bias is the exploratory nature of this study; to our knowledge, there has been little investigation of the possible impact of algorithm bias on technology use. Yet, there is ample evidence to suggest image recognition algorithms exhibit bias against individuals with darker skin (Buolamwini & Gebru, 2018; Ren & Heacock, 2022). If we observe differences in image recognition algorithm use on the basis of skin tone, it will provide motive for future experiments to more conclusively determine the causal role that algorithmic bias plays in the tendency to adopt technology.

To add credence to the idea that algorithmic bias is an underlying mechanism impacting technology use, we have decided to incorporate an additional factor to the present study: algorithm knowledge. *Algorithm knowledge* pertains to an individual's understanding of the mechanisms that contribute to the function of various algorithms. Similar to other digital skills, algorithm knowledge is often tiered with some individuals knowing more about algorithms than others. At its most basic level, algorithm knowledge involves being aware that algorithms exist (*algorithmic awareness*), while more advanced algorithmic knowledge constitutes knowing the principles of algorithm creation and design (Cotter & Reisdorf, 2020). In this study, we define algorithm knowledge as the extent to which individuals possess understanding regarding the factors that influence the operation of facial recognition algorithms and image sensing algorithms. If algorithm knowledge moderates the effect of skin tone on image recognition algorithm use, it would suggest that the ability to detect algorithm bias plays a consequential role in the tendency to adopt algorithms. Increased algorithm knowledge may deter an individual from using biased algorithms, or algorithm knowledge may act as an insulating factor against bias. Individuals with advanced knowledge could potentially navigate around problems stemming from bias, mainly because they can identify shortcomings and adjust their approach accordingly.

Therefore, we ask the following research question:

RQ2. Does algorithm knowledge moderate the relationship between skin tone and image recognition algorithm use?

Pilot Study: Measuring Relative Advantage, Compatibility, Complexity, Observability, Trialability and Reinvention

The pilot study aims to evaluate the construct validity of the measures we created for each of the Diffusion of Innovations (DOI) characteristics. Over the past half-century, DOI has given rise to various methodologies assessing relative advantage, compatibility, complexity, trialability, observability, and reinvention. However, a substantial portion of existing literature either omits an assessment of all six characteristics or narrows its scope considerably, centering primarily on a singular innovation under investigation (de Vries et al., 2018; Finney Rutten et al., 2004; Min et al., 2019; Nehme et al., 2016). Given the rapid development of software-based technologies, there emerges a need for a measure that is both adaptable to new contexts, and comprehensive, covering all six aforementioned DOI characteristics. Such a measure would cultivate a more cohesive comprehension of the DOI traits, enabling researchers to consider them in relation to one another, and allow researchers to easily adapt the measures to emerging technologies. Therefore, prior to conducting our main analysis we conducted a pilot test as the first step to creating a comprehensive and flexible measure of relative advantage, compatibility, complexity, trialability, observability, and reinvention. The pilot test was instrumental in validating the measures for our main analysis.

Method

Participants

We recruited 325 participants from the UCSB Communication SONA subject pool. 61% of the sample identified themselves as women (n = 199), 32% as men (n = 105), 2% as non-binary (n = 5), and 5% didn't specify their gender (n = 16). Participants' ages ranged from 19-25, with an average age of 19.95 (SD = 1.64). 22% identified as Asian (East Asian 58, South Asian 12, Mixed Asian 2), 2% as Black/African American (7), 15% as Latino (49), 38% as White (123), 3.6% as mixed White/Latino (12), and 15% as either mixed race or other (49). Thirteen participants (0.4%) did not specify their race.

Procedure

In order to craft a unified set of questions to assess relative advantage, compatibility, complexity, trialability, observability, and reinvention, we adapted existing DOI measures to form six subscales—one for each of the DOI characteristics and reinvention. To evaluate the adaptability of these questions we then asked participants to respond to the set of questions across four different image recognition contexts: phone unlock, social media filters, financial technology and image sensing technology. Confirmatory factor analyses (CFA) with maximum likelihood estimation were conducted using Mplus (Muthén & Muthén, 2017). We specified and ran four different models, one for each image recognition algorithm context (i.e., Facial recognition for phone unlock, facial recognition for financial systems, facial recognition for social media filters and image sensors), each of which was comprised of six factors, one for each of the diffusion of innovation categories under investigation (i.e., Compatibility, Complexity, Relative Advantage, Observability, Trialability and Reinvention). We used standard fit criteria, considering models with a SRMR $\leq .08$, a CFI and TLI $\geq .95$, and an RMSEA < 0.08 a good fit (Fabrigar et al. 1999; Hu & Bentler, 1999; Brown, 2015).

Measures

Relative advantage. We used four items adapted from adapted from Lin (2011) to assess the degree to which technology is perceived as being better than preceding innovations. Example items include: "[Facial recognition technology] allows (would allow) me to accomplish tasks, such as unlocking my phone, more efficiently" and "[Facial recognition] is (would be) the best way to unlock my phone." We measured responses on a 5-point scale from (1) strongly disagree to (5) strongly agree. (Phone Unlock, *M* = 3.64*, SD* = 0.66; Finances, *M* = 3.70*, SD* = 0.89; Social Media, , *M* = 2.99*, SD* = 0.93; Image Sensors, *M* = 3.58*, SD* = 0.78).

Compatibility. Four items adapted from Huang & Hsieh (2012) evaluated the perceive compatibility of image recognition technology with participants' past experiences, beliefs, and values. Example items include: "[Facial recognition technology] fits (would fit) well with the way that I like to use my phone" and "[Facial recognition technology] is (would be) completely compatible with my current way of using my phone." We measured responses on a 5-point scale from (1) strongly disagree to (5) strongly agree. (Phone Unlock, *M* = 4.05, *SD* = 0.95; Finances, *M* = 3.9, *SD* = 1.05; Social Media, *M* = 3.19, *SD* = 1.16; Image Sensors, *M* = 3.77, *SD* = 0.88).

Complexity. We adapted four items from Moore & Benbasat (1991) to measure perceived complexity of image recognition algorithms. These items assess how participants view the ease or difficulty of understanding a technology. Example items include: "It is (would be) easy to get [facial recognition algorithms] to do what I want them to do when using them to unlock a phone," and "Learning to operate [facial recognition technology] to unlock a phone is (would be) easy for me." We measured responses on a 5-point scale from (1) strongly disagree to (5) strongly agree. (Phone Unlock, *M* = 3.91, *SD* = 0.72; Finances, *M* = 3.87, *SD* = 0.77; Social Media, *M* = 3.68, *SD* = 0.78; Image Sensors, *M* = 3.66, *SD* = 0.76).

Observability. To assess participants' perceived level of observability of facial recognition and image sensing technology, we measured four items related to the degree to which the results of image recognition technologies are observable to others (adapted from Webster et al. 2020). Example items include: "I am (would be) able to observe when others in my environment use facial recognition technology to unlock a phone" and "My friends are (would be) able to observe the results of using facial recognition technology to unlock a phone." We measured responses on a 5-point scale from (1) strongly disagree to (5) strongly agree. (Phone Unlock, $M = 3.42$, $SD = 0.85$; Finances, $M = 2.92$, $SD = 1.02$; Social Media, $M = 3.51$, $SD = 0.95$; Image Sensors, $M = 3.40$, $SD = 0.85$)

Trialability. We adapted four items from Atkinson (2007) to measure perceived trialability, which evaluates the ability to use image recognition technology before deciding to adopt it. Example items include: "I have (anticipate having) the ability to try out facial recognition technology to unlock a phone before deciding whether I like it or not" and "Trying facial recognition to unlock a phone has informed my decision to use facial recognition to unlock a phone." We measured responses on a 5-point scale from (1) strongly disagree to (5) strongly agree. (Phone Unlock, $M = 4.06$, $SD = 0.75$; Finances, $M = 3.70$, $SD = 0.97$; Social Media, $M = 3.64$, $SD = 0.88$; Image Sensors, $M = 3.63$, $SD = 0.84$).

Reinvention. We measured four items adapted from Rogers (2003) to evaluate participants' perceived level of reinvention — the extent to which users change or modify image recognition technology. Example items include: "I often have (anticipate having) to experiment with new ways of using facial recognition technology when using it to unlock my phone" and "I often have (anticipate having) to modify facial recognition technology to get it to work for me when unlocking my phone." We measured responses on a 5-point scale from

(1) strongly disagree to (5) strongly agree. (Phone Unlock, *M* = 2.58*, SD* = 0.84; Finances, *M* = 2.62*, SD* = 0.88; Social Media, *M* = 2.77*, SD* = 0.85; Image Sensors, *M* = 2.85*, SD* = 0.81).

Results

The results of the CFA analysis suggested a reasonable, although not ideal fit, with values of SRMR exceeding 0.08 and TLI/CFI values falling below .95 across all models; RMSEA for all models met acceptable fit criteria, with the RMSEA falling below .08 (Phone unlock: $\chi^2(237) = 538.271$ ($p < .001$) , RMSEA = 0.064, CFI = 0.90, TLI = 0.884, SRMR= 0.086); financial technology: $\chi^2(237) = 586.775$ ($p < .001$), RMSEA = 0.069, CFI = 0.90, TLI = 0.89, SRMR= 0.089), social media filters: $\chi^2(237) = 560.146$ ($p < .001$), RMSEA = 0.066, CFI = 0.92, TLI = 0.90, SRMR= 0.102); image sensors: $\chi^2(237) = 702.263$ ($p < .001$), RMSEA = 0.080, CFI = 0.85, TLI = 0.83, SRMR= 0.103; refer to Table 1 for factor loadings). To improve the model fit, we removed items with factor loadings less than 0.6, based on their modification indices, dropping items with the largest modification indices first. We removed the following items: The third relative advantage question for all contexts, e.g., “The disadvantages of using facial recognition technology to unlock my phone (would) outweigh the advantages”. The fourth complexity measure for all contexts, e.g., “Using facial recognition to unlock a phone is (would be) cumbersome.”. The fourth trialability measure for all contexts, e.g., “I have not had much opportunity to try facial recognition to unlock a phone in the past” and the fourth reinvention measure, e.g., “I rarely have (anticipate having) to come up with novel ways to get facial recognition technology to work for me when using it to unlock my phone” and the first observability measure for phone unlock and image sensor contexts e.g., “Changes in others' use of image sensors (would be) obvious to me”.

Confirmatory factor analysis (CFA) with maximum likelihood estimation were conducted using Mplus (Muthén & Muthén, 2017) on the remaining items. The results of the CFA analysis suggest a good fit of the models on all goodness of fit statistics, with the SRMR less than 0.08 and TLI/CFI values falling above or equal to .95 across all models. As with the initial CFA the RMSEA for all models met acceptable fit criteria, with the RMSEA falling below .08. (Phone unlock: $\chi^2(137) = 223.244$ ($p < .001$), RMSEA = 0.045, CFI = 0.96, TLI = 0.96 SRMR= 0.054; financial technology: $\chi^2(155) = 292$ ($p < .001$), RMSEA = 0.053, CFI = 0.96, TLI = 0.95, SRMR= 0.049; social media filters: $\chi^2(155) = 219.114$ ($p < .001$), RMSEA = 0.036, CFI = 0.98, TLI = 0.98, SRMR= 0.049; image sensors: $\chi^2(137) = 246.513$ ($p < .001$), RMSEA = 0.051, CFI = 0.96, TLI = 0.95, SRMR= 0.050; Refer to table 2 for updated loadings).

Finally, we implemented a second order CFA to ensure items were comparable across the four image recognition contexts. We specified the second order CFA such that each DOI characteristic (i.e., relative advantage, compatibility, complexity, trialability, observability, and reinvention) was comprised of four latent factors representing each of the image recognition algorithm contexts (i.e., phone unlock, social media filters, financial technology and image sensing technology). Each of these contexts was then further delineated by 3 or 4 questions, as established by the preceding CFA (see Figure 1 for conceptual diagram).

The final model was deemed to have acceptable, although not ideal fit with, with an acceptable RMSEA of less than 0.08; however the values of SRMR exceeded 0.08 and TLI/CFI values fell below .95, did not meet the fit criteria ($\chi^2 = 5759.986$ (p <.001), *df* = 2886*, RMSEA* = 0.056*, CFI =,* 0.822 *TIL* = 0.815*, SRMR* = 0.109). This was likely because some of the algorithm contexts had low loadings for certain DOI characteristics (See Table

3). The social media latent factor had a factor loading of 0.389 on relative advantage and a factor loading of 0.364 on compatibility. The image sensor latent factor had a factor loading of 0.42 on observability. Therefore, these items were examined, and their corresponding responses were rephrased with the aim of enhancing clarity. For example, “Facial recognition technology allows me to accomplish tasks on social media more efficiently” was rephrased to “Facial filters allow me to accomplish tasks such as participating in trends on social media more efficiently” for the final experiment. To ensure parsimony, we eliminated two observability items from both the social media and finance contexts so that only three questions are associated with observability in every context. A list of final items can be found in Appendix A. We then proceeded to collect the sample using these new questions for our main analysis.

Discussion

We pursued two primary objectives in this pilot study: (1) to validate the DOI measures before conducting our main study, and (2) to begin developing a flexible scale that can measure relative advantage, compatibility, complexity, trialability, observability, and reinvention across diverse contexts. To achieve these goals, we designed scales with four items each, drawing from existing DOI measures, tailored to four image recognition contexts: phone unlock, social media filters, financial technology, and image sensing technology. We then executed a CFA for each scale's validation, removing items as needed until each scale satisfied the fit criteria. After we validated each context separately, we utilized a higher-order structural equation model to ensure all items corresponded to their designated DOI characteristic when combined. Our findings revealed that certain contexts did not align effectively with some DOI traits. Specifically, the social media context did not align well with relative advantage or compatibility, and the image sensing context did not align well with observability. Consequently, we revised these questions, leading to a final scale featuring three items for relative advantage, complexity, trialability and reinvention questions, and four compatibility questions.

Experiment 1

Methods

Participants. To determine the necessary number of participants for this study, we followed Preacher and Hayes' (2008) recommendation for mediation analysis concerning bootstrapping methods for establishing mediation. Bootstrapping is advantageous as researchers do not have to make assumptions about the sampling distributions of the coefficients or their product (Preacher & Hayes, 2008). Given the analysis's exploratory nature, we chose a small effect for both the total effect and the indirect effect of the independent variable, which corresponds to a 0.14 effect size for both the a and b path. Fritz & MacKinnon (2007) suggest a minimum sample size of at least 558 participants for 80% power and an alpha level of $\alpha = 0.05$. We recruited 851 participants; 41% (352) of the participants identified as female, 56% (477) as male, and the remaining 3% identified as agender (1), male transgender (2), non-binary (14), or chose not to specify (5). The participants had an average age of 36.17 (SD = 12.47), a median income between $50,000 - $59,999, and most had a bachelor's degree as their median education level. 22% of participants self-identified as Asian (East Asian 138, South Asian 46, Mixed Asian 3), 26.6% as Black/African American (227), 18% as Latino (152), 24% as White (205), 6% as mixed White/Latino (50), and 3.4% as mixed race (29). One participant failed to provide a response.

Procedure. We administered an online survey to participants using the Prolific web-based survey platform. Compared to other survey methods like MTurk, SONA student samples, and Qualtrics, participants tend to provide higher-quality data (Douglas et al., 2023). We asked participants about their perceptions of the five DOI characteristics and reinvention across four common image recognition algorithms they encounter daily: facial recognition technology (i.e, phone unlock, social media filters, and financial technology) and image sensing technology (like automatic sensors on water faucets). We also asked about their knowledge of image recognition algorithms and their perceptions of skin tone bias in algorithms.

Measures

Skin Tone. We measured skin tone using the Massey and Martin (2003) scale. Participants selected their skin tone on a 10-point graphic, ranging from light to dark. Campbell et al. (2020) recently validated the reliability and validity of the scale, having raters to two other scales. ($M = 3.6$, $SD = 1.85$).

Relative Advantage. We used three items adapted from adapted from Lin (2011) to assess the degree to which technology is perceived as being better than preceding innovations. Examples include: "[Facial recognition technology] allows me to unlock my phone more efficiently" and "[Facial recognition] is the best way to unlock my phone". We scored responses on a 5-point scale from (1) strongly disagree to (5) strongly agree. (Phone Unlock, $\alpha = 0.93$, $M = 3.29$, $SD = 1.36$; Finances, $\alpha = 0.93$, $M = 3.05$, $SD = 1.35$; Social Media, $\alpha = 0.90$, $M = 2.72$, $SD = 1.23$; Image Sensors, $\alpha = 0.90$, $M = 3.55$, $SD = 1.08$).

Compatibility. Four items, adapted from Huang & Hsieh (2012), measured how participants perceive the compatibility of image recognition technology with their past experiences, beliefs, and values. Example items include: “[Facial recognition technology] fits well with the way I like to use my phone” and “[Facial recognition technology] suits my needs when unlocking my phone”. We scored responses on a 5-point scale from (1) strongly disagree to (5) strongly agree. (Phone Unlock, α = 0.97, M = 3.39, SD = 1.43; Finances, α = 0.97, M = 3.08, SD = 1.44; Social Media, α = 0.96, M = 2.68, SD = 1.36; Image Sensors, α = 0.94, M = 3.84, SD = 1.06).

Complexity. We adapted three items from Moore & Benbasat (1991) to measure the perceived complexity. These items assess how participants view the ease or difficulty of understanding a technology. Example items include: “It's easy to get [facial recognition] algorithms to do what I want when using them to unlock a phone” and “Learning to operate [facial recognition] technology to unlock a phone is easy for me”. We scored responses on a 5-point scale from (1) strongly disagree to (5) strongly agree. (Phone Unlock, α = 0.89, M = 3.91, SD = 1.00; Finances, α = 0.92, M = 3.63, SD = 1.12; Social Media, α = 0.89, M = 3.75, SD = 1.00; Image Sensors, α = 0.87, M = 3.96, SD = 0.93).

Observability. To assess participants' perceived level of observability of facial recognition and image sensing technology, we measured three items related to the degree to which the results of image recognition technologies are observable to others, adapted from Webster et al. (2020). Examples include: “I can observe when others in my environment use [facial recognition technology] to unlock a phone” and “My friends can observe the results of using [facial recognition technology] to unlock a phone”. We scored responses on a 5-point scale from (1) strongly disagree to (5) strongly agree. (Phone Unlock, α = 0.92, M = 3.64, SD = 1.09; Finances, α = 0.92, M = 2.96, SD = 1.20; Social Media, α = 0.90, M = 3.73, SD = 1.04; Image Sensors, α = 0.91, M = 4.09, SD = 0.94).

Trialability. We adapted three items from Atkinson (2007) to measure perceived trialability, which evaluates the ability to use image recognition technology before deciding to adopt it. Example items include: "I can try out [facial recognition technology] to unlock a phone before deciding whether I like it" and "Trying [facial recognition] to unlock a phone has informed my decision to use it". We scored responses on a 5-point scale from (1) strongly disagree to (5) strongly agree. (Phone Unlock, $\alpha = 0.84$, M = 3.79, SD = 1.13; Finances, $\alpha = 0.88$, M = 3.27, SD = 1.28; Social Media, $\alpha = 0.83$, M = 3.72, SD = 1.07; Image Sensors, $\alpha = 0.80$, M = 3.87, SD = 0.95).

Reinvention. We measured three items adapted from Rogers (2003) to evaluate participants' perceived level of reinvention — the extent to which users change or modify image recognition technology. Example items include: "I often experiment with new ways of using [facial recognition technology] when unlocking my phone" and "I often modify [facial recognition technology] to make it work when unlocking my phone". We scored responses on a 5-point scale from (1) strongly disagree to (5) strongly agree. (Phone Unlock, $\alpha = 0.80$, M = 3.74, SD = 1.07; Finances, $\alpha = 0.82$, M = 3.09, SD = 1.20; Social Media, $\alpha = 0.79$, M = 3.62, SD = 1.02; Image Sensors, $\alpha = 0.77$, M = 3.88, SD = 0.96).

Algorithm use. We assessed the use of image recognition algorithms by asking participants how often they use 17 facial and image recognition technologies. We measured responses on a 5-point scale from *never to always*. **(**Facial Recognition Technology Use**,** $M = 2.42$, SD = 1.07; Image Sensor Technology Use**,** $M = 3.01$, SD = 0.81**).** For full list of items see appendix A.

Algorithm knowledge. We assessed participants' algorithm knowledge by asking them how different factors influence the output of facial recognition and image sensing technology. We adapted the question from Cotter and Reindorf (2020) and based the answers on current literature that discusses the factors influencing image recognition algorithms. Example items include: "Lighting conditions of the environment" and "Other phenotypical features, such as your face shape". We scored responses on a 5-point scale from (1) *strongly disagree* to (5) *strongly agree.* (Facial Recognition, α = 0.68, M = 3.53, SD = 0.78; Image Sensors, α = 0.68, M = 3.62, SD = 0.78). For full list of items see appendix A

Perceived skin tone bias in algorithms. We assessed participants' perceived skin tone bias in algorithms by asking them how strongly they agreed with the following question (modified from Calice et al., 2021): "Results from image recognition algorithms are distorted by skin tone bias in AI systems". We scored responses on a 5-point scale from (1) *strongly disagree* to (5) *strongly agree* (M = 3.07, SD = 1.27). For full list of items see appendix A.

Results

The hypothesis and analysis plan for this study were preregistered using Open Science Framework. For the results of all pre-registered analyses, see appendix B. All model coefficients that are reported are in unstandardized form following the recommendation of Hayes, (2013, p. 200).

Hypothesis 1 posited that the relationship between skin tone and image recognition algorithm use is mediated by perceived relative advantage, such that those with lighter skin tones perceive more relative advantage than those with darker skin tones, thus increasing the use of image recognition algorithms among users with lighter skin tones. We used PROCESS Model 4 with a 5000-sample bootstrap to conduct a mediation analysis for a model that included skin tone as the independent variable (IV), relative advantage as the mediator (M), and image recognition algorithm use as the dependent variable (DV).

Contrary to our prediction, our data show that individuals with darker skin use image recognition algorithms more frequently than those with lighter skin tones. As can be seen in Figures 2-5, participants with darker skin tones tended to perceive image recognition algorithms as having greater relative advantage than those with lighter skin tones (a [phone unlock] = 0.055, $p < .05$; a [finances] = 0.085, $p < .001$], a [social media filters] = 0.098, $p < .001$; a [image sensors] = 0.041, $p < .05$) and participants who perceived greater relative advantage were more likely to use image recognition algorithms (b [phone unlock] = 0.527, $p < .001$; b [finances] = 0.527, $p < .001$; b [social media filters] = 0.468, $p < .001$; b [image sensors] = 0.200, $p < .001$).

The bias-corrected bootstrap confidence interval indicated that there was a significant indirect effect for phone unlock (ab = 0.029, 95% CI [0.0028, 0.0564]), finances (ab = 0.045, 95% CI [0.0177, 0.0718]) and social media filters (ab = 0.046, 95% CI [0.0251, 0.0682]) but not for image sensors (ab = 0.008, 95% CI [-0.001, 0.0175]). Lastly, the results provided mixed evidence regarding whether skin tone directly influenced image recognition algorithm usage apart from relative advantage (c' [phone unlock] = 0.055, $p < .01$; c' [finances] = 0.034, $p < .05$; c' [social media filters] = 0.033, $p > .05$; c' [image sensors] = 0.015, $p > .05$).

Hypothesis 2 posited that that the relationship between skin tone and image recognition algorithm use would be mediated by perceived compatibility, such that those with lighter skin tones would perceive more compatibility than those with darker skin tones, thus increasing use of image recognition algorithms among users with lighter skin tones. We used PROCESS Model 4 with a 5000-sample bootstrap to conduct a mediation analysis for a model that included skin tone as the independent variable (IV), compatibility as the mediator (M), and image recognition algorithm use as the dependent variable (DV).

Contrary to our prediction, our data show that individuals with darker skin tones use image recognition algorithms more frequently than those with lighter skin tones. As can be seen in figures 6-9, participants with darker skin tones tended to perceive image recognition algorithms as having greater compatibility than those with lighter skin tones (*a* [phone unlock] = 0.079, $p < .01$; *a* [finances] = 0.091, $p < .001$], *a* [social media filters] = 0.091, $p < .001$; *a* [image sensors] = 0.021, $p > .05$) and participants who perceived greater relative advantage were more likely to use image recognition algorithms (*b* [phone unlock] = 0.482, $p < .001$; *b* [finances] = 0.484, $p < .001$; *b* [social media filters] = 0.448, $p < .001$; *b* [image sensors] = 0.232, $p < .001$).

The bias-corrected bootstrap confidence interval indicated that there was a significant indirect effect for phone unlock (*ab* = 0.037 , 95% CI [0.0118, 0.0625]), finances (*ab* = 0.044, 95% CI [0.0177, 0.0693]) and social media filters (*ab* = 0.0407, 95% CI [0.018, 0.0642]) but not for image sensors (*ab* = 0.005, 95% CI [-0.005, 0.0148]). Lastly, the results provided mixed evidence regarding whether skin tone directly influenced image recognition algorithm usage apart from compatibility (*c'* [phone unlock] = 0.041, $p < .01$; *c'* [finances] = 0.035, $p < .05$; *c'* [social media filters] = 0.038, $p < .05$; *c'* [image sensors] = 0.019, $p > .05$).

Hypothesis 3 posited that the relationship between skin tone and image recognition algorithm use would be mediated by perceived complexity, such that those with lighter skin tones would perceive less complexity than those with darker skin tones, thus increasing use of image recognition algorithms among users with lighter skin tones. We used PROCESS Model 4 with a 5000-sample bootstrap to conduct a mediation analysis for a model that included skin tone as the independent variable (IV), complexity as the mediator (M), and image recognition algorithm use as the dependent variable (DV).

Contrary to our prediction, our data show that individuals with darker skin tones use image recognition algorithms more frequently than those with lighter skin tones. As can be seen in figures 10-13, participants with darker skin tones tended to perceive image recognition algorithms as being easier to use (less complexity) than those with lighter skin tones (*a* [phone unlock] = 0.019, p >.05; *a* [finances] = 0.041, $p < .05$], *a* [social media filters] = 0.039, $p < .05$; *a* [image sensors] = 0.024, $p > .05$) and participants who perceived image recognition algorithms as being easier to use (less complexity) were more likely to use image recognition algorithms (*b* [phone unlock] = 0.417, $p < .001$; *b* [finances] = 0.436, $p < .001$; *b* [social media filters] = 0.338, $p < .001$; *b* [image sensors] = 0.157, $p < .001$).

However, the bias-corrected bootstrap confidence interval indicated that there only a significant indirect effect for social media filters (*ab* = 0.0132, 95% CI [0.018, 0.0265]), but not for phone unlock (*ab* = 008, 95% CI [-0.0075, 0.0228]), finances (*ab* = 0.018, 95% CI [-0.0001, 0.0353]) or image sensors (*ab* = 0.0037, 95% CI [-0.0023, 0.0102]). Lastly, the results indicated that skin tone directly influenced image recognition algorithm usage apart from complexity (*c'* [phone unlock] = 0.07, $p < .001$; *c'* [finances] = 0.059, $p < .001$; *c'* [social media filters] = 0.067, $p < .001$; *c'* [image sensors] = 0.023, $p > .05$).

Hypothesis 4 posited that that the relationship between skin tone and image recognition algorithm use would be mediated by perceived observability, such that those with lighter skin tones would perceive more observability than those with darker skin tones, thus increasing use of image recognition algorithms among users with lighter skin tones. We used PROCESS Model 4 with a 5000-sample bootstrap to conduct a mediation analysis for a model that included skin tone as the independent variable (IV), observability as the mediator (M), and image recognition algorithm use as the dependent variable (DV).

Contrary to our prediction, our data show that individuals with darker skin tones use image recognition algorithms more frequently than those with lighter skin tones. As can be seen in figures 14-17, participants with darker skin tones tended to perceive image recognition algorithms as having greater observability than those with lighter skin tones (a [phone unlock] = 0.060, $p < .01$; a [finances] = 0.078, $p < .001$], a [social media filters] = 0.057, $p < .001$; a [image sensors] = 0.002, $p > .05$) and participants who perceived greater observability were more likely to use image recognition algorithms (b [phone unlock] = 0.346, $p < .001$; b [finances] = 0.380, $p < .001$; b [social media filters] = 0.218, $p < .001$; b [image sensors] = 0.159, $p < .001$).

The bias-corrected bootstrap confidence interval indicated that there was a significant indirect effect for phone unlock (ab = 0.0208, 95% CI [0.007, 0.0353]), finances (ab = 0.03, 95% CI [0.0125, 0.048]) and social media filters (ab = 0.0124, 95% CI [0.0032, 0.0224]) but not for image sensors (ab = 0.0003, 95% CI [-0.0063, 0.0063]). Lastly, the results indicated that skin tone directly influenced image recognition algorithm usage apart from observability (c' [phone unlock] = 0.058, $p < .001$; c' [finances] = 0.048, $p < .01$; c' [social media filters] = 0.066, $p < .05$; c' [image sensors] = 0.023, $p > .05$).

Hypothesis 5 posited that those with lighter skin tones would engage in reinvention of image recognition algorithms that uses image recognition algorithms less often than those with darker skin tones. We conducted a linear regression to obtain results for a model that included skin tone as the independent variable (IV) and reinvention of image recognition algorithms as the dependent variable (DV).

The results aligned with the relationship we predicted in Hypothesis 5. Across all four contexts, individuals with lighter skin tones engaged in reinvention less frequently than those with darker skin tones (Phone Unlock [Adjusted $R^2 = 0.012$, $\beta = 0.073$, $p < .001$], Finances [Adjusted $R^2 = 0.013$, $\beta = 0.076$, $p < .001$], Social Media Filters [Adjusted $R^2 = 0.032$, $\beta = 0.119$, $p < .001$], Image Sensors: [Adjusted $R^2 = 0.007$, $\beta = 0.058$, $p < .01$]). These findings remained significant when we controlled for general technology use and income across all facial recognition contexts, and when we accounted for income in the image sensors context. See tables 4-7.

Research question 1 asked if perceptions of skin tone bias is associated with trialability. We conducted a linear regression to obtain results for a model that included skin tone as the independent variable (IV) and trialability of image recognition algorithms as the dependent variable (DV).

Our results indicated that the perception of skin tone bias correlated with trialability in the context of finances (Adjusted $R^2 = 0.007$, $\beta = -0.093$, $p < .01$), but not for phone unlock (Adjusted $R^2 = -0.001$, $\beta = -0.012$, $p = 0.697$), social media facial filters (Adjusted $R^2 = -0.00$, $\beta = -0.00$, $p = 0.628$) or image sensors (Adjusted $R^2 = -0.001$, $\beta = -0.011$, $p = 0.663$).

Research question 2 asked if algorithm knowledge moderated the relationship between skin tone and image recognition algorithm use. We assessed knowledge of algorithms in two main categories: facial recognition algorithms and image sensing algorithms. To examine how the level of algorithm knowledge (M) influences the relationship between skin tone (IV) and image recognition algorithm use (DV), we employed a moderation analysis using PROCESS Model 1 with a 5000-sample bootstrap.

As can be seen in table 8, results indicate that algorithm knowledge does moderate the relationship between skin tone and image recognition algorithms use for facial recognition technology ($p < .01$) but not for image sensing technology ($p = .08$). We explored this interaction at three levels of algorithm knowledge: one standard deviation above the mean (+1 SD), at the mean (M), and one standard deviation below the mean (-1 SD). The findings indicate a significant impact of skin tone on technology use when algorithm knowledge is one standard deviation above the mean ($\beta = 0.13$, $p < .001$), and at the mean ($\beta = 0.074$, $p < .001$). However, this influence is not observed when algorithm knowledge is one standard deviation below the mean ($\beta = 0.017$, $p = 0.52$). As illustrated in figure 18, the effect of skin tone on the use of image recognition algorithms depends on algorithm knowledge. Specifically, participants who had high algorithm knowledge, but not those who had low algorithm knowledge, used image recognition algorithms more as skin tone darkens.

Post hoc exploratory tests

Following our initial analysis results, we conducted post hoc exploratory tests, extending our original hypotheses. Firstly, given the confirmation of the positive relationship between skin tone and reinvention in Hypothesis 5, we explored the potential mediating role of reinvention between skin tone and image recognition algorithm use. DOI theory proposes that reinvention bolsters innovation adoption (Rogers, 2003). If those with darker skin tones are reinventing image recognition algorithms to their needs (as exhibited in Hypothesis 5), it would likely lead to increased usage of those algorithms.

Secondly, given the results of RQ2, which showed that algorithm knowledge moderated the relationship between skin tone and image recognition use, such that as participants who had above average algorithm knowledge, but not those who had below average algorithm knowledge, used image recognition algorithms more as skin tone darkens.

We decided to test if algorithm knowledge moderated the mediated relationships found in H1, H2 and H4. Such models include skin tone as the independent variable (IV), either compatibility, relative advantage, observability, or reinvention of facial recognition algorithms as the mediator (M), and facial recognition algorithm use as the dependent variable (DV). Algorithm knowledge (of facial recognition algorithms) acted as the moderator (W) between skin tone (IV), and the DOI characteristics (M).

While our initial analysis involved investigating perceptions of DOI characteristics in three distinct facial recognition contexts (phone unlock, financial systems, and social media) and one image recognition context, our post hoc analysis took a different approach. We consolidated these three facial recognition contexts into a single, overarching global facial recognition context. This simplification was aimed at maintaining clarity for the post hoc tests and was achieved by aggregating the responses across each context (i.e., phone unlock, financial systems, and social media) and computing their average for each DOI characteristic.

Post hoc test 1: Mediation of reinvention

We used PROCESS Model 4 with a 5000-sample bootstrap to conduct a mediation analysis for a model with skin tone as the independent variable (IV), reinvention as the mediator (M), and image recognition algorithm use as the dependent variable (DV).

As can be seen in Figures 19-20, participants with darker skin tones tended to engage in reinvention more than those with light skin tones (a [facial recognition algorithms] = 0.090, $p < .001$; a [image sensors] = 0.061, $p < .01$) and participants who engaged in reinvention more frequently were more likely to use image recognition algorithms (b [facial recognition algorithms] = 0.546, $p < .001$; b [image sensors] = 0.138, $p < .001$).

The bias-corrected bootstrap confidence interval indicated that there was a significant indirect effect for both facial recognition algorithms (*ab* = 0.049, 95% CI [0.027, 0.071]), and image sensors (*ab* = 0.0085, 95% CI [0.0020, 0.0167]). Lastly, the results showed that skin tone did not directly influence image recognition algorithm usage apart from reinvention (*c'* [facial recognition algorithms] = 0.029, $p > .05$; *c'* [image sensors] = 0.013, $p > .05$).

Post hoc test 2: Moderated mediation of algorithm knowledge on compatibility, relative advantage, observability, and reinvention

We created five separate models, one for each of the original mediation models (i.e., compatibility, relative advantage, observability, complexity) and one for reinvention. We used PROCESS Model 7 with a 5000-sample bootstrap to conduct a moderated mediation analysis for each model. The models included skin tone as the independent variable (IV), either compatibility, relative advantage, observability, complexity or reinvention of facial recognition algorithms as the mediator (M), and facial recognition algorithm use as the dependent variable (DV). Algorithm knowledge (of facial recognition algorithms) acted as the moderator (W) between skin tone (IV), and the DOI characteristics (M).

As can be seen in tables 9-13 our data shows that for facial recognition algorithms, individuals with darker skin tones and greater algorithm knowledge are more likely to perceive facial recognition algorithms as having more relative advantage (*a* at -1SD = 0.005, p = 0.87; at Mean = 0.072, p = <.001, at +SD = 0.139, p = <.001), compatibility (*a* at -1SD = -0.009, p = 0.77; *a* at Mean = 0.078, p = <.001, *a* at +SD =0 .166, p = <.001), observability (*a* at -1SD = 0.002, p = 0.948; *a* at Mean = 0.036, p = <.05, *a* at +SD =0 .071, p = <.01) and complexity (*a* at -1SD = -0.005, p = 0.833; *a* at Mean = 0.029, p = 0.073, *a* at +SD = 0.064, p = <.01). Similarly, individuals with darker skin tones and greater levels of algorithm knowledge were more likely to engage in reinvention (*a* at -1SD = 0.014, p = 0.3; *a* at Mean = 0.082, p = <.001, *a* at +SD = 0 .137, p = <.001). Participants who perceived more relative advantage, compatibility, observability, less complexity and who were more likely to engage in reinvention of facial recognition algorithms were more likely to use facial recognition algorithms (*b* [relative advantage] = 0.736, $p < .001$; *b* [compatibility] = 0.674, $p < .001$; *b* [observability] = 0.536, $p < .001$; *b* [complexity] = 0.569, $p < .001$; *b* [reinvention] = 0.541, $p < .001$).

The bias-corrected bootstrap confidence interval indicated that there was a significant moderated mediation for compatibility (*index of moderated mediation* = 0.075, 95% CI [0.038, 0.112]), relative advantage (*index of moderated mediation* = 0.063, 95% CI [0.022, 0.101]), and reinvention (*index of moderated mediation* = 0.038, 95% CI [0.013, 0.062]), such that as algorithm knowledge increased, so did the effect of skin tone on facial recognition algorithm use through compatibility (*conditional moderated mediation of algorithm knowledge* at -1SD = -0.006, 95% CI [-0.047, 0.038]*;* at Mean = 0.053, 95% CI [0.024, 0.082]; at +1SD = 0.112, 95% CI [0.071, 0.151]), relative advantage (*conditional moderated mediation of algorithm knowledge* at -1SD = 0.003, 95% CI [-0.039, 0.051]*;* at Mean = 0.053, 95% CI [0.023, 0.083]; at +1SD = 0.102, 95% CI [0.061, 0.144]) and reinvention (*conditional moderated mediation of algorithm knowledge* at -1SD = 0.014, 95% CI [-0.011, 0.042]*;* at Mean = 0.044, 95% CI [0.024, 0.066]; at +1SD = 0.074, 95% CI [0.044, 0.104]). We did not find a significant moderated mediation for observability (*index of moderated mediation* = 0.022, 95% CI [-0.004, 0.047]) or complexity (*index of moderated mediation* = 0.025, 95% CI [-0.006, 0.052])

Similar to facial recognition algorithms, we created five separate models for image sensing algorithms, one for compatibility, relative advantage, observability, complexity and reinvention. We used PROCESS Model 7 with a 5000-sample bootstrap to conduct a moderated mediation analysis for each model. The models included skin tone as the independent variable (IV), either compatibility, relative advantage, observability, complexity or reinvention of image sensing algorithms as the mediator (M), and image sensing algorithms use as the dependent variable (DV). Algorithm knowledge (of image sensing algorithms) acted as the moderator (W) between skin tone (IV), and the DOI characteristics (M).

As can be seen in tables 14-16 our data shows that for image sensing algorithms, individuals with darker skin tones and greater algorithm knowledge are more likely to perceive image sensing algorithms as having more relative advantage (a at -1SD = -0.020, p = 0.454; at Mean = 0.031, p = 0.122, at +SD = 0.083, p = <.01) and compatibility (a at -1SD = -0.046, p = 0.09; a at Mean = 0.012, p = 0.522, a at +SD = 0.072, p = <.01) and were more likely to engage in reinvention (a at -1SD = 0.014, p = 0.3; a at Mean = 0.082, p = <.001, a at +SD = 0 .137, p = <.001). Participants who perceived more relative advantage and compatibility and who were more likely to engage in reinvention of image sensing algorithms were more likely to use image sensing algorithms (b [relative advantage] = 0.196, $p < .001$; b [compatibility] = 0.23, $p < .001$; b [reinvention] = 0.140, $p < .001$). We did not find a significant moderation effect for observability or complexity.

The bias-corrected bootstrap confidence interval indicated that there was a significant moderated mediation for compatibility (*index of moderated mediation* = 0.018, 95% CI [0.003, 0.031]), relative advantage (*index of moderated mediation* = 0.013, 95% CI [0.001, 0.025]), and reinvention (*index of moderated mediation* = 0.008, 95% CI [0.001, 0.017]), such that as algorithm knowledge increased, so did the effect of skin tone on image sensing algorithm use through compatibility (*conditional moderated mediation of algorithm knowledge* at -1SD = -0.010, 95% CI [-0.024, 0.004]*;* at Mean = 0.003, 95% [-0.007, 0.013]; at +1SD = 0.017, 95% CI [0.002, 0.031]), relative advantage (*conditional moderated mediation of algorithm knowledge* at -1SD = -0.004, 95% CI [-0.016, 0.009]*;* at Mean = 0.006, 95% CI [-0.002, 0.015]; at +1SD = 0.016, 95% CI [0.004, 0.029]) and reinvention (*conditional moderated mediation of algorithm knowledge* at -1SD = 0.001, 95% CI [-0.006, 0.010]*;* at Mean = 0.008, 95% CI [0.001, 0.016]; at +1SD = 0.015, 95% CI [0.005, 0.026]).

Discussion

This study aimed to investigate the influence of algorithm bias on technology adoption and use. We utilized diffusion of innovations to examine the relationship between skin tone and the use of specific image recognition algorithms that are known to exhibit skin tone bias. According to DOI, the adoption and utilization of technology, such as image recognition algorithms, hinge on how users perceive that technology. We hypothesized that, due to known skin tone bias in certain image recognition algorithms, people with darker skin tones would perceive the technology as having less relative advantage (hypothesis 1), less compatibility (hypothesis 2), more complexity (hypothesis 3) and less observability (hypothesis 4) and would thus use image recognition technologies less.

Key findings

Our results refuted this assumption. Although relative advantage (for facial recognition algorithms), compatibility (for facial recognition algorithms), complexity (for facial recognition algorithms used on social media only) and observability (for facial recognition algorithms) did significantly mediate the relationship between skin tone and image recognition algorithm use, those with darker skin tones tended to perceive *more* relative advantage, *more* compatibility, *less* complexity and *more* observability and thus used image recognition technologies more than those with lighter skin tones. Furthermore, we found that perceptions of skin tone bias were not associated with trialability (RQ1), except in the context of finances.

This seeming paradox, where individuals who are more likely to be affected by algorithmic biases are also more likely to adopt these technologies, may indicate adaptive resilience. Our analysis of Hypothesis 5 showed a higher propensity among those with darker skin tones to engage in reinvention. Further exploratory analysis confirmed that reinvention positively mediates the relationship between skin tone and image recognition algorithm use, such that those with darker skin tones are more likely to engage in reinvention and thus use image recognition algorithms more frequently.

Our research also found that having algorithm knowledge influenced how skin tone relates to image recognition algorithm use (RQ2). Specifically, individuals with darker skin tones and average or higher algorithm knowledge use facial recognition algorithms more often (though not image sensing algorithms) that those with lighter skin tones. Our exploratory extends this finding further, finding that among those with darker skin tones, a higher degree of algorithm knowledge correlated with enhanced perceptions of relative advantage, compatibility, and reinvention for both facial recognition and image sensing algorithms. As a result, the usage of both types of algorithms rose (as indicated by moderated mediation).

Implications

Why does algorithm knowledge and reinvention seem to increase the use of image recognition technology only for those with darker skin tones? One possibility is that individuals with darker skin tones, being constantly impacted by algorithm bias, are forced to spend more time adapting their behavior to get image recognition technologies to work for them (reinvention). A byproduct of this may be that the time spent reinventing the technology then increases their understanding of the algorithms (algorithm knowledge). This possibility aligns with DOI, which posits that reinvention allows users to make changes to an innovation to suit their needs better, which in turn contributes to greater adoption of the innovation (Rogers, 2003). An alternative explanation for these findings may not be rooted in algorithm bias. Cultural or other factors may influence algorithm knowledge and reinvention among individuals with darker skin tones. The cause of these results should be empirically investigated by subsequent research.

Another implication of our findings suggests that the flexibility of image recognition algorithms could reduce the negative effects of algorithmic bias. According to DOI, innovations that are perceived as a more general concept that can solve a wide range of problems are more prone to reinvention (Rogers, 2003). When software is malleable, users, especially those who historically encounter bias, like individuals with darker skin tones, can reinvent it to bypass or correct biases. However, this workaround is notably absent in more inflexible technologies. Addressing biases at the developmental phase becomes even more critical in domains where technology lacks this malleability. As such, while software adaptability offers a safety net for image recognition biases, it underscores the urgent need to proactively counteract bias across all technological areas.

Limitations

These data present certain limitations that are important to address. Firstly, this paper faces the problem of multiple comparisons; given the number of tests done, it is likely that at least one of the results is erroneous. More pointed hypotheses and fewer analyses are an essential next step in minimizing type one error. Secondly, the mediation analysis in this study should only be taken as a preliminary investigation of these issues (Chan et al. 2022), and future studies should strive to empirically validate the causality of these results through an experiment. Thirdly, these data are limited by the nature of the study. Although it is well established that many image recognition algorithms exhibit skin tone bias (Ajmal et al., 2021; Buolamwini & Gebru, 2018; Ray et al., 2021; Ren & Heacock, 2022) we are unable to quantify the level of bias present in the image recognition algorithms under investigation. We also were unable to disentangle perceptions of bias verses actual bias. Future studies should manipulate both bias perception and the actual bias present in algorithms to gain a comprehensive understanding of how algorithmic bias affects algorithm adoption and use. Finally, while we asked participants about how much they perceive themselves to be reinventing technology, we did not explore the mechanisms by which this occurred. It is always possible that perceived reinvention does not correspond to actual reinvention. Future studies should look at how algorithm users engage in reinvention.

Conclusion

As technology advances, our interactions with the world are increasingly mediated by algorithms that are often biased. This study aimed to examine the potential impact that algorithm bias can have on downstream technology adoption and use. Our findings demonstrate that users can overcome these biases, suggesting that reinvention and algorithm knowledge may be used to curb some of the negative effects presented by bias. Although these findings are encouraging, they are preliminary. Additional work must be done to better understand the effects of algorithm bias and minimize its negative effects as we continue to move further into the algorithm age.

References

Ajmal, Boonya-Ananta, T., Rodriguez, A. J., Du Le, V. N., & Ramella-Roman, J. C. (2021). Monte carlo analysis of optical heart rate sensors in commercial wearables: The effect of skin tone and obesity on the photoplethysmography (PPG) signal. *Biomedical Optics Express*, *12*(12), 7445–7457. https://doi.org/10.1364/BOE.439893

Amazon Science (2021). National Science Foundation, in collaboration with Amazon, awards 11 Fairness in AI grant projects. *Amazon Science*. Retrieved September 13, 2022, from https://www.amazon.science/academic-engagements/national-science-foundation-in-collaboration-with-amazon-awards-11-fairness-in-ai-grant-projects

AWS (2023) *Facial Recognition: What is it and why it's important,* Amazon Web Services, Inc. Retrieved September 20, 2023, from https://aws.amazon.com/what-is/facial-recognition/

Azoulay, A. (2018). Towards an ethics of artificial intelligence. *United Nations*. Retrieved September 13, 2022, from https://www.un.org/en/chronicle/article/towards-ethics-artificial-intelligence

Barocas, S., & Selbst, A. D. (2016). Big data's disparate impact. *Calif. L. Rev.*, *104*, 671.

Barr, A. (2015). Google mistakenly tags black people as 'gorillas,' showing limits of algorithms. *The Wall Street Journal*. Retrieved October 24, 2022, from https://www.wsj.com/articles/BL-DGB-42522

Biagas, D. E., & Bianchi, A. J. (2016). The Latin americanization thesis: An expectation states approach. *Social Forces*, *94*(3), 1335–1358.

Brown, T. A. (2015). *Confirmatory factor analysis for applied research*. Guilford publications.

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, 2018.

By: IBM Cloud Education. (n.d.). What is machine learning? *IBM*. Retrieved September 12, 2022, from https://www.ibm.com/cloud/learn/machine-learning

Calice, M. N., Bao, L., Freiling, I., Howell, E., Xenos, M. A., Yang, S., Brossard, D., Newman, T. P., & Scheufele, D. A. (2021). Polarized platforms? How partisanship shapes perceptions of "algorithmic news bias." *New Media & Society*, 14614448211034160. https://doi.org/10.1177/14614448211034159

Campbell, M. E., Keith, V. M., Gonlin, V., & Carter-Sowell, A. R. (2020). Is a picture worth a thousand words? An experiment comparing observer-based skin tone measures. *Race and Social Problems*, *12*(3), 266–278. https://doi.org/10.1007/s12552-020-09294-0

Chan, M., Hu, P., & K. F. Mak, M. (2022). Mediation Analysis and Warranted Inferences in Media and Communication Research: Examining Research Design in Communication Journals From 1996 to 2017. *Journalism & Mass Communication Quarterly*, *99*(2), 463–486. https://doi.org/10.1177/1077699020961519

Cialdini, R. B. (2007). Influence: The psychology of persuasion. Rev. ed.; 1st. In 1984 (Ed.), *Collins business essentials* (pp. 87-125). New York, Collins.

Corno, L. (1986). The metacognitive control components of self-regulated learning. *Contemporary Educational Psychology*, *11*(4), 333–346. https://doi.org/10.1016/0361-476X(86)90029-9

Cotter, K. (2021). “Shadowbanning is not a thing”: Black box gaslighting and the power to independently know and credibly critique algorithms. *Information, Communication & Society*, 1–18.

Cotter, K., & Reisdorf, B. C. (2020). Algorithmic knowledge gaps: A new dimension of (digital) inequality. *International Journal of Communication (19328036)*, *14*.

Danks, D., & London, A. J. (2017). Algorithmic bias in autonomous systems. *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence*, 4691–4697. https://doi.org/10.24963/ijcai.2017/654

Dastin, J. (2018). Amazon scraps secret AI recruiting tool that showed bias against women. *Reuters*. Retrieved September 13, 2022, from https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G

Dearing J. W. & Singhal A. (2020). New directions for diffusion of innovations research: Dissemination, implementation, and positive deviance. *Human Behavior and Emerging Technologies*, *2*, 307–313. https://doi.org/10.1002/hbe2.216

De-Arteaga, M., Fogliato, R., & Chouldechova, A. (2020). A Case for Humans-in-the-Loop: Decisions in the Presence of Erroneous Algorithmic Scores. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–12. https://doi.org/10.1145/3313831.3376638

DeVito, M. A., Birnholtz, J., Hancock, J. T., French, M., & Liu, S. (2018). How people form folk theories of social media feeds and what it means for how we study self-presentation. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 1–12. https://doi.org/10.1145/3173574.3173694

de Vries, H., Tummers, L., & Bekkers, V. (2018). The Diffusion and Adoption of Public Sector Innovations: A Meta-Synthesis of the Literature. *Perspectives on Public Management and Governance*, *1*(3), 159–176. https://doi.org/10.1093/ppmgov/gvy001

Douglas, B. D., Ewell, P. J., & Brauer, M. (2023). Data quality in online human-subjects research: Comparisons between MTurk, Prolific, CloudResearch, Qualtrics, and SONA. *PLOS ONE*, *18*(3), e0279720. https://doi.org/10.1371/journal.pone.0279720

Epstein, M.D, R. H. (2021, May 20). Can a Smartwatch Save Your Life? *The New York Times*. https://www.nytimes.com/2021/05/20/well/live/smartwatch-heart-rate-monitor.html

Eslami, M., Rickman, A., Vaccaro, K., Aleyasen, A., Vuong, A., Karahalios, K., Hamilton, K., & Sandvig, C. (2015). "I always assumed that I wasn't really that close to [her]": Reasoning about Invisible Algorithms in News Feeds. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 153–162. https://doi.org/10.1145/2702123.2702556

Federal Agencies Digitization Guidelines Initiative (n.d.) *Sensor—Glossary*. Retrieved September 20, 2023, from https://www.digitizationguidelines.gov/term.php?term=sensor

Finney Rutten, L. J., Nelson, D. E., & Meissner, H. I. (2004). Examination of population-wide trends in barriers to cancer screening from a diffusion of innovation perspective

(1987–2000). *Preventive Medicine*, *38*(3), 258–268. https://doi.org/10.1016/j.ypmed.2003.10.011

Fosch-Villaronga, E., Poulsen, A., Søraa, R. A., & Custers, B. (2021). Gendering algorithms in social media. *SIGKDD Explor. Newsl.*, *23*(1), 24–31. https://doi.org/10.1145/3468507.3468512

Fritz, M. S., & MacKinnon, D. P. (2007). Required Sample Size to Detect the Mediated Effect. *Psychological Science*, *18*(3), 233–239. https://doi.org/10.1111/j.1467-9280.2007.01882.x

Google Search Central (2023). *Google*. Retrieved February 28, 2023, from https://developers.google.com/search/docs/fundamentals/how-search-works

Gran, A.-B., Booth, P., & Bucher, T. (2021). To be or not to be algorithm aware: A question of a new digital divide? *Information, Communication & Society*, *24*(12), 1779–1796. https://doi.org/10.1080/1369118X.2020.1736124

Grother, P., Ngan, M., & Hanaoka, K. (2019). *Face recognition vendor test part 3: Demographic effects* (NIST IR 8280; p. NIST IR 8280). National Institute of Standards and Technology. https://doi.org/10.6028/NIST.IR.8280

Hamilton, K. A. (2020). *The extended organism: A framework for examining strategic media skill in a digital ecology* (Doctoral dissertation). University of Illinois at Urbana-Champaign.

Hamilton, M. (2019). The sexist algorithm. *Behavioral Sciences & the Law*, *37*(2), 145–157. https://doi.org/10.1002/bsl.2406

Hayes, A. F. (2013). Introduction to Mediation, Moderation, and Conditional Process Analysis, First Edition: A Regression-Based Approach. United States: Guilford Publications.

Hill, K. (2020). Another arrest, and jail time, due to a bad facial recognition match. *The New York Times*. Retrieved September 20, 2022, from https://www.nytimes.com/2020/12/29/technology/facial-recognition-misidentify-jail.html

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural equation modeling: a multidisciplinary journal, 6(1), 1-5

Huang, L.-Y., & Hsieh, Y.-J. (2012). Consumer electronics acceptance based on innovation attributes and switching costs: The case of e-book readers. *Electronic Commerce Research and Applications*, *11*(3), 218–228. https://doi.org/10.1016/j.elerap.2011.12.005

Johnson, K. (2022). Feds warn employers against discriminatory hiring algorithms. *Wired*. Retrieved August 4, 2022, from https://www.wired.com/story/ai-hiring-bias-doj-eecc-guidance/#:~:text=Hiring%20algorithms%20can%20penalize%20applicants,to%20interact%20with%20a%20keyboard

Kirkpatrick, K. (2016). Battling algorithmic bias: How do we ensure algorithms treat us fairly? *Communications of the ACM*, *59*(10), 16–17. https://doi.org/10.1145/2983270

Klare, B. F., Burge, M. J., Klontz, J. C., Vorder Bruegge, R. W., & Jain, A. K. (2012). Face Recognition Performance: Role of Demographic Information. *IEEE Transactions on*

Information Forensics and Security, *7*(6), 1789–1801. https://doi.org/10.1109/TIFS.2012.2214212

Knight, W. (2019). The Apple Card didn't 'see' gender-and that's the problem. *Wired*. Retrieved August 4, 2022, from https://www.wired.com/story/the-apple-card-didnt-see-genderand-thats-the-problem/

Kuncel, N. R., Klieger, D. M., Connelly, B. S., & Ones, D. S. (2013). Mechanical versus clinical data combination in selection and admissions decisions: A meta-analysis. *Journal of Applied Psychology*, *98*(6), 1060–1072. https://doi.org/10.1037/a0034156

Laqueur, H. S., & Copus, R. W. (2022). An algorithmic assessment of parole decisions. *Journal of Quantitative Criminology*. https://doi.org/10.1007/s10940-022-09563-8

Larson, J., Angwin, J., Kirchner, L., & Mattu, S. (2016). How we analyzed the compas recidivism algorithm. *ProPublica*. Retrieved October 24, 2022, from https://www.propublica.org/article/how-we-analyzed-the-compas-recidivism-algorithm

Lin, H. F. (2011). An empirical investigation of mobile banking adoption: The effect of innovation attributes and knowledge-based trust. *International journal of information management, 31(3),* 252-260.

Lomborg, S., & Kapsch, P. H. (2020). Decoding algorithms. *Media, Culture & Society*, *42*(5), 745–761. https://doi.org/10.1177/0163443719855301

Lynn, S. K., & Barrett, L. F. (2014). "Utilizing" signal detection theory. *Psychological Science*, *25*(9), 1663–1673. https://doi.org/10.1177/0956797614541991

Lythreatis, S., Singh, S. K., & El-Kassar, A.-N. (2022). The digital divide: A review and future research agenda. *Technological Forecasting and Social Change*, *175*, 121359. https://doi.org/10.1016/j.techfore.2021.121359

Massey, D. S., & Martin, J. A. (2003). The NIS Skin Color Scale. Retrieved March 24, 2023, from https://nis.princeton.edu/downloads/NIS-Skin-Color-Scale.pdf.

Massoomi, M. R., & Handberg, E. M. (2019). Increasing and Evolving Role of Smart Devices in Modern Medicine. *European Cardiology Review*, *14*(3), 181–186. https://doi.org/10.15420/ecr.2019.02

Mihelj, S., Leguina, A., & Downey, J. (2019). Culture is digital: Cultural participation, diversity and the digital divide. *New Media & Society*, *21*(7), 1465–1485. https://doi.org/10.1177/1461444818822816

Min, S., So, K. K. F., & Jeong, M. (2019). Consumer adoption of the uber mobile application: Insights from diffusion of innovation theory and technology acceptance model. *Journal of Travel & Tourism Marketing*, *36*(7), 770–783. https://doi.org/10.1080/10548408.2018.1507866

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research, 2(3)*, 192-222

Muthén, L.K. and Muthén, B.O. (1998-2017). Mplus User's Guide. Eighth Edition. Los Angeles, CA: Muthén & Muthén

Nehme, E. K., Pérez, A., Ranjit, N., Amick, B. C., & Kohl, H. W. (2016). Behavioral theory and transportation cycling research: application of diffusion of innovations. *Journal of Transport & Health*, *3*(3), 346–356. https://doi.org/10.1016/j.jth.2016.05.127

Noble, S. U. (2018). *Algorithms of oppression: How search engines reinforce racism*. New York, NY: New York University Press.

Obermeyer Z., Powers B., Vogeli C., & Mullainathan S., (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, *366*(6464), 447–453. https://doi.org/10.1126/science.aax2342

Pardes, A. (2019). This dating app exposes the monstrous bias of algorithms. *Wired*. Retrieved August 4, 2022, from https://www.wired.com/story/monster-match-dating-app/

Pew Research Center (2016) 1. demographic trends and economic well-being. *Pew Research Center's Social & Demographic Trends Project*. Retrieved January 10, 2023, from https://www.pewresearch.org/social-trends/2016/06/27/1-demographic-trends-and-economic-well-being/

Pew Research Center (2017). Code-dependent: Pros and cons of the algorithm age. *https://www.pewresearch.org/internet/2017/02/08/code-dependent-pros-and-cons-of-the-algorithm-age/*

Pew Research Center (2018). Public attitudes toward computer algorithms. *Pew Research Center.* https://www.pewresearch.org/internet/2018/11/16/public-attitudes-toward-computer-algorithms/

Pew Research Center (2022). Home broadband adoption, computer ownership vary by race, ethnicity in the U.S. *Pew Research Center*. Retrieved January 10, 2023, from https://www.pewresearch.org/fact-tank/2021/07/16/home-broadband-adoption-computer-ownership-vary-by-race-ethnicity-in-the-u-s/

Preacher, K. J., & Hayes, A. F. (2008). Contemporary Approaches to Assessing Mediation in Communication Research. In A. Hayes, M. Slater, & L. Snyder, *The SAGE Sourcebook* *of Advanced Data Analysis Methods for Communication Research* (pp. 13–54). Sage Publications, Inc. https://doi.org/10.4135/9781452272054.n2

Rabassa, V., Sabri, O., & Spaletta, C. (2022). Conversational commerce: Do biased choices offered by voice assistants' technology constrain its appropriation? *Technological Forecasting and Social Change*, *174*, 121292. https://doi.org/10.1016/j.techfore.2021.121292

Rajkomar, A., Oren, E., Chen, K., Dai, A. M., Hajaj, N., Hardt, M., Liu, P. J., Liu, X., Marcus, J., Sun, M., Sundberg, P., Yee, H., Zhang, K., Zhang, Y., Flores, G., Duggan, G. E., Irvine, J., Le, Q., Litsch, K., … Dean, J. (2018). Scalable and accurate deep learning with electronic health records. *Npj Digital Medicine*, *1*(1), Article 1. https://doi.org/10.1038/s41746-018-0029-1

Ray, I., Liaqat, D., Gabel, M., & de Lara, E. (2021). Skin tone, Confidence, and Data Quality of Heart Rate Sensing in WearOS Smartwatches. *2021 IEEE International Conference on Pervasive Computing and Communications Workshops and Other Affiliated Events (PerCom Workshops)*, 213–219. https://doi.org/10.1109/PerComWorkshops51409.2021.9431120

Reisdorf, B. C., & Blank, G. (2021). Algorithmic literacy and platform trust. In E. Hargittai (Ed.), *Handbook of digital inequality* (pp. 341-357). Edward Elgar Publishing.

Ren Q., & Heacock, H. (2022). Sensitivity of infrared sensor faucet on different skin colours and how it can potentially effect equity in public health. *BCIT Environmental Public Health Journal*. https://doi.org/10.47339/ephj.2022.216

Rice, R. E. (2017). Intermediality and the diffusion of innovations: Intermediality and the diffusion of innovations. *Human Communication Research*, *43*(4), 531–544. https://doi.org/10.1111/hcre.12119

Rogers, E. M. (2003). *Diffusion of innovations: 5th ed* (5th ed.). Free Press.

Rosenfeld, M. J., Thomas, R. J., & Hausen, S. (2019). Disintermediating your friends: How online dating in the United States displaces other ways of meeting. *Proceedings of the National Academy of Sciences*, *116*(36), 17753–17758. https://doi.org/10.1073/pnas.1908630116

Royer, J. M. (1979). Theories of the transfer of learning. *Educational Psychologist*, *14*(1), 53–69. https://doi.org/10.1080/00461527909529207

Scherr, S., Haim, M., & Arendt, F. (2019). Equal access to online information? Google's suicide-prevention disparities may amplify a global digital divide. *New Media & Society*, *21*(3), 562–582. https://doi.org/10.1177/1461444818801010

Sweeney, L. (2013). Discrimination in online ad delivery. *Communications of the ACM*, *56*(5), 44–54.

U.S. Equal Employment Opportunity Commission (2022) The Americans with disabilities act and the use of software, algorithms, and artificial intelligence to assess job applicants and employees. *US EEOC*. Retrieved September 13, 2022, from https://www.eeoc.gov/laws/guidance/americans-disabilities-act-and-use-software-algorithms-and-artificial-intelligence

UNESCO (2020). UNESCO launches worldwide online public consultation on the Ethics of Artificial Intelligence. *UNESCO*. Retrieved September 13, 2022, from https://en.unesco.org/news/unesco-launches-worldwide-online-public-consultation-ethics-artificial-intelligence

Vagnani, G., Gatti, C., & Proietti, L. (2019). A conceptual framework of the adoption of innovations in organizations: A meta-analytical review of the literature. *Journal of Management and Governance*, *23*(4), 1023–1062. https://doi.org/10.1007/s10997-019-09452-6

Victor, D. (2016, March 24). Microsoft Created a Twitter Bot to Learn From Users. It Quickly Became a Racist Jerk. *The New York Times*. https://www.nytimes.com/2016/03/25/technology/microsoft-created-a-twitter-bot-to-learn-from-users-it-quickly-became-a-racist-jerk.html

Vlasceanu, M., & Amodio, D. M. (2022). Propagation of societal gender inequality by internet search algorithms. *Proceedings of the National Academy of Sciences*, *119*(29), e2204529119. https://doi.org/10.1073/pnas.2204529119

Wang, R., Harper, F. M., & Zhu, H. (2020). Factors influencing perceived fairness in algorithmic decision-making algorithm outcomes*, Development Procedures, and Individual Differences*. 14.

Webster, C. A., Mîndrilă, D., Moore, C., Stewart, G., Orendorff, K., & Taunton, S. (2020). Measuring and Comparing Physical Education Teachers' Perceived Attributes of CSPAPs: An Innovation Adoption Perspective. *Journal of Teaching in Physical Education*, *39*(1), 78–90. https://doi.org/10.1123/jtpe.2018-0328

Wilson, B., Hoffman, J., & Morgenstern, J. (2019). Predictive inequity in object detection. *arXiv preprint arXiv:1902.11097*.

Ytre-Arne, B., & Moe, H. (2021). Folk theories of algorithms: Understanding digital irritation. *Media, Culture & Society*, *43*(5), 807–824. https://doi.org/10.1177/0163443720972314

Zhang, L., & Yencha, C. (2022). Examining perceptions towards hiring algorithms. *Technology in Society*, *68*, 101848. https://doi.org/10.1016/j.techsoc.2021.101848

Zhang, M. (2015a). *Google photos tags two African-Americans as gorillas through Facial Recognition Software*. Forbes. Retrieved September 20, 2022, from https://www.forbes.com/sites/mzhang/2015/07/01/google-photos-tags-two-african-americans-as-gorillas-through-facial-recognition-software/?sh=70b7114713d8

Zhang, M. (2015b). *Flickr Fixing "Racist" Auto-Tagging Feature After Black Man Mislabeled "Ape" | PetaPixel*. PetaPixel. Retrieved September 20, 2023, from https://petapixel.com/2015/05/20/flickr-fixing-racist-auto-tagging-feature-after-black-man-mislabeled-ape/

Zhang, S., Wu, Y., & Chang, J. (2020). Survey of image recognition algorithms. *2020 IEEE 4th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC)*, 542–548. https://doi.org/10.1109/ITNEC48623.2020.9084972

Zou, J., & Schiebinger, L. (2018). AI can be sexist and racist—It's time to make it fair. *Nature*, *559*(7714), 324–326. https://doi.org/10.1038/d41586-018-05707-8

Table 1

Factor loadings for initial CFA

Social Media			**Image Sensors**			**Financial Systems**			**Phone Unlock**		
param	**est**	**se**	**param**	**est**	**se**	**param**	**est**	**se**	**param**	**est**	**se**
RS1	.893	0.019	RI1	.848	.025	RF1	.792	.035	RU1	.785	.032
RS2	.88	0.019	RI2	.812	.034	RF2	.75	.032	RU2	.815	.028
RS3	**.101**	**0.077**	**RI3**	**.216**	**.077**	**RF3**	**.359**	**.069**	**RU3**	**.328**	**.067**
RS4	.875	0.025	RI4	.812	.031	RF4	.88	.021	RU4	.771	.042
CS1	.893	0.019	CI1	.872	.022	CF1	.915	.015	CU1	.896	.02
CS2	.906	0.016	CI2	.891	.018	CF2	.896	.019	CU2	.889	.024
CS3	.94	0.01	CI3	.872	.022	CF3	.934	.013	CU3	.895	.019
CS4	.932	0.014	CI4	.895	.019	CF4	.907	.023	CU4	.917	.017
COS1	.771	0.034	COI1	.662	.044	COF1	.741	.039	COU1	.622	.046
COS2	.866	0.025	COI2	.829	.031	COF2	.886	.024	COU2	.821	.031
COS3	.861	0.029	COI3	.872	.028	COF3	.902	.025	COU3	.882	.032
COS4	**.117**	**0.067**	**COI4**	**.276**	**.069**	**COF4**	**.192**	**.064**	**COU4**	**.154**	**.064**
TS1	.797	0.038	TI1	.784	.046	TF1	.753	.05	TU1	.553	.134
TS2	0.712	0.054	TI2	.824	.046	TF2	.777	.054	TU2	.598	.155
TS3	0.779	0.047	TI3	.648	.065	TF3	.78	.05	TU3	.746	.127
TS4	**.284**	**0.087**	**TI4**	**.207**	**.086**	**TF4**	**.439**	**.086**	**TU4**	**.413**	**.172**
OS1	.792	0.038	**OI1**	**.55**	**.059**	OF1	.704	.048	**OU1**	**.565**	**.053**
OS2	.87	0.026	OI2	.794	.05	OF2	.802	.039	OU2	.788	.033
OS3	.901	0.018	OI3	.9	.023	OF3	.851	.036	OU3	.801	.036
OS4	.858	0.023	OI4	.829	.033	OF4	.871	.024	OU4	.748	.042

RES1	.795	0.036	REI1	.85	.05	REF1	.802	.041	REU1	.81	.049
RES2	.874	0.03	REI2	.72	.053	REF2	.763	.047	REU2	.756	.048
RES3	.785	0.041	REI3	.669	.056	REF3	.798	.045	REU3	.668	.052
RES4	**.05**	**.081**	**REI4**	**.14**	**.085**	**REF4**	**.135**	**.074**	**REU4**	**.075**	**.076**

Note, variables are named according to their, DOI characteristic, context and their question number. R = Relative advantage, C = Compatibility, CO = Complexity, T = Trialability, O = Observability, RE = Reinvention. S = Social media, I = Image sensor, F = Finical systems, U = Phone unlock. Bolded items indicate poor fit

Table 2

Factor loadings for second CFA

Social Media			**Image Sensors**			**Financial Systems**			**Phone Unlock**		
param	**est**	**se**	**param**	**est**	**se**	**param**	**est**	**se**	**param**	**est**	**se**
RS1	.893	.019	RI1	.846	.025	RF1	.791	0.035	RU1	.782	.032
RS2	.88	.019	RI2	.813	.034	RF2	.75	0.031	RU2	.814	.028
RS4	.875	.025	RI4	.813	.031	RF4	.882	0.021	RU4	.774	.041
CS1	.893	.019	CI1	.871	.022	CF1	.915	0.015	CU1	.896	.02
CS2	.906	.016	CI2	.891	.018	CF2	.895	0.019	CU2	.889	.024
CS3	.94	.01	CI3	.872	.022	CF3	.934	0.013	CU3	.896	.019
CS4	.932	.014	CI4	.895	.019	CF4	.907	0.023	CU4	.917	.017
COS1	.773	.034	COI1	.662	.044	COF1	.741	0.039	COU1	.63	.045
COS2	.866	.026	COI2	.828	.032	COF2	.883	0.024	COU2	.821	.031
COS3	.86	.029	COI3	.874	.028	COF3	.905	0.024	COU3	.879	.032

TS1	.799	.037	TI1	.795	.039	TF1	.771	0.042	TU1	.657	.065
TS2	.73	.048	TI2	.835	.041	TF2	.82	0.042	TU2	.725	.072
TS3	.754	.046	TI3	.623	.058	TF3	.725	0.046	TU3	.597	.075
OS1	.792	.038	OI2	.792	.05	OF1	.704	0.048	OU2	.795	.034
OS2	.869	.026	OI3	.925	.022	OF2	.801	0.039	OU3	.816	.036
OS3	.901	.018	OI4	.81	.035	OF3	.851	0.036	OU4	.73	.046
OS4	.858	.023				OF4	.871	.024			
RES1	.796	.036	REI1	.858	.05	REF1	.804	.042	REU1	.798	.049
RES2	.873	.03	REI2	.712	.053	REF2	.76	.047	REU2	.767	.046
RES3	.784	.041	REI3	.665	.057	REF3	.798	.045	REU3	.67	.052

Note, variables are named according to their, DOI characteristic, context and their question number. R = Relative advantage, C = Compatibility, CO = Complexity, T = Trialability, O = Observability, RE = Reinvention. S = Social media, I = Image sensor, F = Financial systems, U = Phone unlock. Bold variables have questionable loadings

Table 3

Factor loadings for final higher-order CFA

Relative Advantage			Compatibility			Complexity			Trialability			Observability			Reinvention		
	est.	se		est.	se		est.	se		est.	se		est.	se		est.	se
RU1	.763	.036	CU1	.894	.021	COU1	.62	.043	TU1	.671	.061				REU1	.748	.044
RU2	.825	.029	CU2	.886	.025	COU2	.832	.029	TU2	.729	.057	OU2	.79	.037	REU2	.742	.04
			CU3	.898	.02	COU3	.875	.032	TU3	.581	.065	OU3	.794	.036	REU3	.747	.04
RU4	.781	.04	CU4	.918	.017							OU4	.756	.045			
RF1	.808	.038	CF1	.914	.016	COF1	.742	.038	TF1	.788	.04	OF1	.696	.047	REF1	.794	.034

RF2	.722	0.036	CF2	.896	.02	COF2	.886	.024	TF2	.835	.038	OF2	.794	.039	REF2	.78	.036
			CF3	.933	.013	COF3	.902	.021	TF3	.688	.046	OF3	.857	.033	REF3	.788	.035
RF4	.885	.024	CF4	.908	.024							OF4	.875	.022			
RS1	.887	.023	CS1	.89	.021	COS1	.748	.037	TS1	.82	.037	OS1	.791	.039	RES1	.769	.041
RS2	.899	.02	CS2	.908	.016	COS2	.888	.024	TS2	.729	.05	OS2	.865	.027	RES2	.858	.033
			CS3	.935	.013	COS3	.855	.03	TS3	.733	.049	OS3	.9	.018	RES3	.82	.042
RS4	.863	.029	CS4	.938	.013							OS4	.863	.022			
RI1	.83	.032	CI1	.869	.026	COI1	.621	.046	TI1	.812	.037				REI1	.793	.055
RI2	.829	.033	CI2	.894	.019	COI2	.832	.033	TI2	.826	.043	OI2	.784	.051	REI2	.695	.054
			CI3	.873	.024	COI3	.892	.024	TI3	.61	.056	OI3	.929	.025	REI3	.75	.052
RI4	.814	.03	CI4	.892	.02							OI4	.812	.037			
Phone Unlock	.75	.05	Phone Unlock	.697	.055	Phone Unlock	.767	.052	Phone Unlock	.67	.084	Phone Unlock	.68	.07	Phone Unlock	.908	.032
Financial	.805	.053	Financial	.714	.059	Financial	.821	.038	Financial	.697	.066	Financial	.689	.088	Financial	.93	.034
Social Media	**.389**	**.078**	**Social Media**	**.364**	**.077**	Social Media	.709	.059	Social Media	.721	.068	Social Media	.638	.073	Social Media	.796	.048
Image Sensors	.557	.07	Image Sensors	.59	.057	Image Sensors	.733	.048	Image Sensors	.596	.075	**Image Se0nsors**	**.42**	**.093**	Image Sensors	.692	.065

Note, variables are named according to their, DOI characteristic, context, and their question number. R = Relative advantage, C = Compatibility, CO = Complexity, T = Trialability, O = Observability, RE = Reinvention. S = Social media, I = Image sensor, F = Financial systems, U = Phone unlock. Bold variables have questionable loadings

Table 4

H5 Linear Regression. IV Skin Tone, DV Reinvention for Phone Unlock

Covariates	Adjusted R^2	β	*SE*	*t*	*p*	95% CI
None	0.012	0.073	0.022	3.350	<0.000	[0.030, 0.116]
Income	0.031	0.074	0.022	3.412	<0.000	[0.031, 0.117]
Technology Use	0.073	0.047	0.022	2.155	0.031	[0.004, 0.090]
Income and Technology Use	0.078	0.049	0.022	2.23	0.026	[0.005, 0.091]

Table 5

H5 Linear Regression. IV Skin Tone, DV Reinvention for Finances

Covariates	Adjusted R^2	β	*SE*	*t*	*p*	95% CI
None	0.013	0.076	0.022	3.499	<0.000	[0.033, 0.119]
Income	0.027	0.080	0.022	3.668	<0.000	[0.037, 0.122]
Technology Use	0.069	0.053	0.022	2.442	0.015	[0.010, 0.096]
Income and Technology Use	0.071	0.057	0.022	2.61	0.009	[0.005, 0.091]

Table 6

H5 Linear Regression. IV Skin Tone, DV Reinvention for Social Media

Covariates	Adjusted R^2	β	*SE*	*t*	*p*	95% CI
None	0.032	0.119	0.022	5.435	<0.000	[0.075, 0.160]
Income	0.068	0.122	0.021	5.72	<0.000	[0.08, 0.164]
Technology Use	0.099	0.094	0.021	4.40	<0.000	[0.010, 0.096]
Income and Technology Use	0.113	0.102	0.021	4.71	<0.000	[0.059, 0.143]

Table 7

H5 Linear Regression. IV Skin Tone, DV reinvention for Image Sensors

Covariates	Adjusted R^2	β	*SE*	*t*	*p*	95% CI

None	0.007	0.058	0.022	2.700	0.007	[0.016, 0.100]
Income	0.038	0.062	0.021	2.898	0.004	[0.020, 0.104]
Technology Use	0.078	0.034	0.021	1.589	0.112	[-0.00, 0.076]
Income and Technology Use	0.089	0.039	0.021	1.812	0.070	[-0.003, 0.083]

Table 8

RQ2 Moderation Analysis: IV Skin Tone, DV Facial Recognition Technology Use, Moderator Algorithm Knowledge Facial Recognition Algorithms

Predictor	β	*SE*	*t*	*p*	95% CI
Skin Tone	-0.180	0.085	-2.107	0.035	[-0.347, -0.012]
Algorithm Knowledge: Facial Recognition	-0.229	0.099	-2.313	0.021	[-0.424, -0.035]
Skin Tone * Algorithm Knowledge: Facial Recognition	0.071	0.023	3.123	0.002	[0.027, 0.117]
Conditional Effects of Skin Tone at Values of Algorithm Knowledge Facial Recognition Algorithms on Global Facial Recognition Technology Use					
Predictor	**β**	***SE***	***t***	***p***	**95% CI**
-1 SD	0.017	0.028	0.641	0.52	[-0.036, 0.072]
Mean	0.074	0.0198	3.746	<0.000	[0.035, 0.113]
+1 SD	0.130	0.026	5.092	<0.000	[0.080, 0.181]

Table 9

Moderated Mediation: Algorithm knowledge and Relative Advantage Facial Recognition

Direct Relationships	***β***	***t***	***p***
Skin Tone → Global Facial Recognition Technology Use	0.022	1.714	0.087
Skin Tone → Relative Advantage Facial Recognition	-0.231	-2.61	0.009
Relative Advantage Facial Recognition → Global Facial Recognition Technology Use	0.736	33.33	0.000
Skin Tone*Algorithm Knowledge → Relative Advantage Facial Recognition	0.086	3.605	0.000

Probing the Interaction Effect of Skin Tone*Algorithm Knowledge on Relative Advantage

Level of the Moderator	***β***	***SE***	***t***	***p***

-1 SD	0.005	0.029	0.166	0.868
Mean	0.072	0.021	3.507	0.000
+1 SD	0.139	0.026	5.257	0.000
Index of Moderated mediation		***SE***	***95% CI***	
0.0633		0.020	[0.022, 0.101]	
Indirect Effect of Skin Tone on Global Facial Recognition Technology Use Through Relative Advantage				
Level of the Moderator	***Effect***	***SE***	***95% CI***	
-1 SD	0.003	0.023	[-0.039, 0.051]	
Mean	0.053	0.015	[0.023, 0.083]	
+1 SD	0.102	0.021	[0.061, 0.144]	

Table 10

Moderated Mediation: Algorithm Knowledge and Compatibility Facial Recognition

Direct Relationships		***β***	***t***	***p***
Skin Tone → Global Facial Recognition Technology Use		0.021	1.607	0.108
Skin Tone → Compatibility Facial Recognition		-0.317	-3.365	0.001
Compatibility Facial Recognition → Global Facial Recognition Technology Use		0.674	31.994	0.000
Skin Tone*Algorithm Knowledge → Compatibility Facial Recognition		0.112	4.400	0.000
Probing the Interaction Effect of Skin Tone*Algorithm Knowledge on Compatibility				
Level of the Moderator	***β***	***SE***	***t***	***p***
-1 SD	-0.009	0.031	-0.291	0.771
Mean	0.078	0.022	3.570	0.000
+1 SD	0.166	0.028	5.835	0.000
Index of Moderated mediation		***SE***	***95% CI***	
0.075		0.019	[0.038, 0.112]	
Indirect Effect of Skin Tone on Global Facial Recognition Technology Use Through Relative Advantage				
Level of the Moderator	***Effect***	***SE***	***95% CI***	
-1 SD	-0.006	0.023	[-0.047, 0.038]	
Mean	0.053	0.015	[0.024, 0.082]	
+1 SD	0.112	0.021	[0.071, 0.151]	

Table 11

Moderated Mediation: Algorithm Knowledge and Observability Facial Recognition

Direct Relationships	***β***	***t***	***p***

Skin Tone → Global Facial Recognition Technology Use	0.046	2.554	0.010
Skin Tone → Observability Facial Recognition	-0.087	-1.263	0.206
Observability Facial Recognition → Global Facial Recognition Technology Use	0.536	13.915	0.000
Skin Tone*Algorithm Knowledge → Observability Facial Recognition	0.041	2.208	0.027

Probing the Interaction Effect of Skin Tone*Algorithm Knowledge on Observability				
Level of the Moderator	***β***	***SE***	***t***	***p***
-1 SD	0.002	0.025	0.065	0.948
Mean	0.036	0.018	2.032	0.042
+1 SD	0.071	0.023	3.083	0.002
Index of Moderated mediation		***SE***	***95% CI***	
		0.013	[-0.004, 0.047]	

Table 12

Moderated Mediation: Algorithm knowledge and Complexity Facial Recognition

Direct Relationships	***β***	***t***	***p***
Skin Tone → Global Facial Recognition Technology Use	0.062	3.543	0.000
Skin Tone → Complexity Facial Recognition	-0.125	-1.768	0.077
Complexity Facial Recognition → Global Facial Recognition Technology Use	0.569	15.063	0.000
Skin Tone*Algorithm Knowledge → Complexity Facial Recognition	0.043	2.288	0.022

Probing the Interaction Effect of Skin Tone*Algorithm Knowledge on Complexity				
Level of the Moderator	***β***	***SE***	***t***	***p***
-1 SD	-0.005	0.023	-0.211	0.833
Mean	0.029	0.016	1.794	0.073
+1 SD	0.064	0.021	2.987	0.003
Index of Moderated mediation		***SE***	***95% CI***	
0.0248		0.015	[-0.006, 0.052]	

Table 13

Moderated Mediation: Algorithm Knowledge and Reinvention Facial Recognition

Direct Relationships	***β***	***t***	***p***
Skin Tone → Global Facial Recognition Technology Use	0.030	1.743	0.082

Skin Tone → Reinvention Facial Recognition		-0.163	-2.037	0.041
Reinvention Facial Recognition → Global Facial Recognition Technology Use		0.541	17.011	0.000
Skin Tone*Algorithm Knowledge → Reinvention Facial Recognition		0.069	3.210	0.001
Probing the Interaction Effect of Skin Tone*Algorithm Knowledge on Reinvention				
Level of the Moderator	***β***	***SE***	***t***	***p***
-1 SD	0.027	0.026	1.039	0.299
Mean	0.082	0.019	4.385	0.000
+1 SD	0.137	0.024	5.639	0.000
Index of Moderated mediation		***SE***	***95% CI***	
0.0376		0.012	[0.013, 0.062]	
Indirect Effect of Skin Tone on Global Facial Recognition Technology Use Through Reinvention				
Level of the Moderator	***Effect***	***SE***	***95% CI***	
-1 SD	0.014	0.013	[-0.011, 0.042]	
Mean	0.044	0.010	[0.024, 0.066]	
+1 SD	0.074	0.015	[0.044, 0.104]	

Table 14

Moderated Mediation: Algorithm Knowledge and Relative Advantage: Image Sensors

Direct Relationships		***β***	***t***	***p***
Skin Tone → Global Image Sensor Use		0.015	1.060	0.289
Skin Tone → Relative Advantage Image Sensors		-0.212	-2.384	0.017
Relative Advantage Image Sensors → Global Image Sensor Use		0.196	7.797	0.000
Skin Tone*Algorithm Knowledge → Relative Advantage Image Sensors		0.067	2.841	0.005
Probing the Interaction Effect of Skin Tone*Algorithm Knowledge on Relative Advantage				
Level of the Moderator	***β***	***SE***	***t***	***p***
-1 SD	-0.020	0.028	-0.748	0.454
Mean	0.031	0.020	1.547	0.122
+1 SD	0.083	0.027	3.135	0.002
Index of Moderated mediation		***SE***	***95% CI***	
		0.020	[0.001, 0.025]	
Indirect Effect of Skin Tone on Global Image Sensor Use Through Relative Advantage				
Level of the Moderator	***Effect***	***SE***	***95% CI***	
-1 SD	-0.004	0.006	[-0.016, 0.009]	
Mean	0.006	0.004	[-0.002, 0.015]	

+1 SD	0.016	0.006	[0.004, 0.029]

Table 15

Moderated Mediation: Algorithm Knowledge and Compatibility: Image Sensors

Direct Relationships		***β***	***t***	***p***
Skin Tone → Global Image Sensor Use		0.018	1.282	0.200
Skin Tone → Compatibility Image Sensors		-0.265	-3.02	0.003
Compatibility Image Sensors → Global Image Sensor Use		0.23	9.135	0.000
Skin Tone*Algorithm Knowledge → Compatibility Image Sensors		0.076	3.286	0.001
Probing the Interaction Effect of Skin Tone*Algorithm Knowledge on Compatibility				
Level of the Moderator	***β***	***SE***	***t***	***p***
-1 SD	-0.046	0.028	-1.693	0.091
Mean	0.012	0.020	0.639	0.522
+1 SD	0.072	0.026	2.743	0.002
Index of Moderated mediation		***SE***	***95% CI***	
		0.007	[0.003, 0.031]	
Indirect Effect of Skin Tone on Global Facial Recognition Technology Use Through Compatibility				
Level of the Moderator	***Effect***	***SE***	***95% CI***	
-1 SD	-0.010	0.007	[-0.024, 0.004]	
Mean	0.003	0.005	[-0.007, 0.013]	
+1 SD	0.017	0.007	[0.002, 0.031]	

Table 16

Moderated Mediation: Algorithm Knowledge and Reinvention: Image Sensors

Direct Relationships		***β***	***t***	***p***
Skin Tone → Global Image Sensor Use		0.011	0.783	0.434
Skin Tone → Reinvention Image Sensors		-0.163	-1.713	0.087
Reinvention Image Sensors → Global Image Sensor Use		0.140	5.880	0.000
Skin Tone*Algorithm Knowledge → Reinvention Image Sensors		0.060	2.400	0.017
Probing the Interaction Effect of Skin Tone*Algorithm Knowledge on Reinvention				
Level of the Moderator	***β***	***SE***	***t***	***p***
-1 SD	0.009	0.030	0.328	0.742
Mean	0.057	0.022	2.629	0.008
+1 SD	0.105	0.029	3.643	0.000
Index of Moderated mediation		***SE***	***95% CI***	

		0.004	[0.001, 0.017]
Indirect Effect of Skin Tone on Global Facial Recognition Technology Use Through Reinvention			
Level of the Moderator	***Effect***	***SE***	***95% CI***
-1 SD	0.001	0.004	[-0.006, 0.010]
Mean	0.008	0.004	[0.001, 0.016]
+1 SD	0.015	0.005	[0.005, 0.026]

Figures

Figure 1

Conceptual diagram of the higher order factor analysis

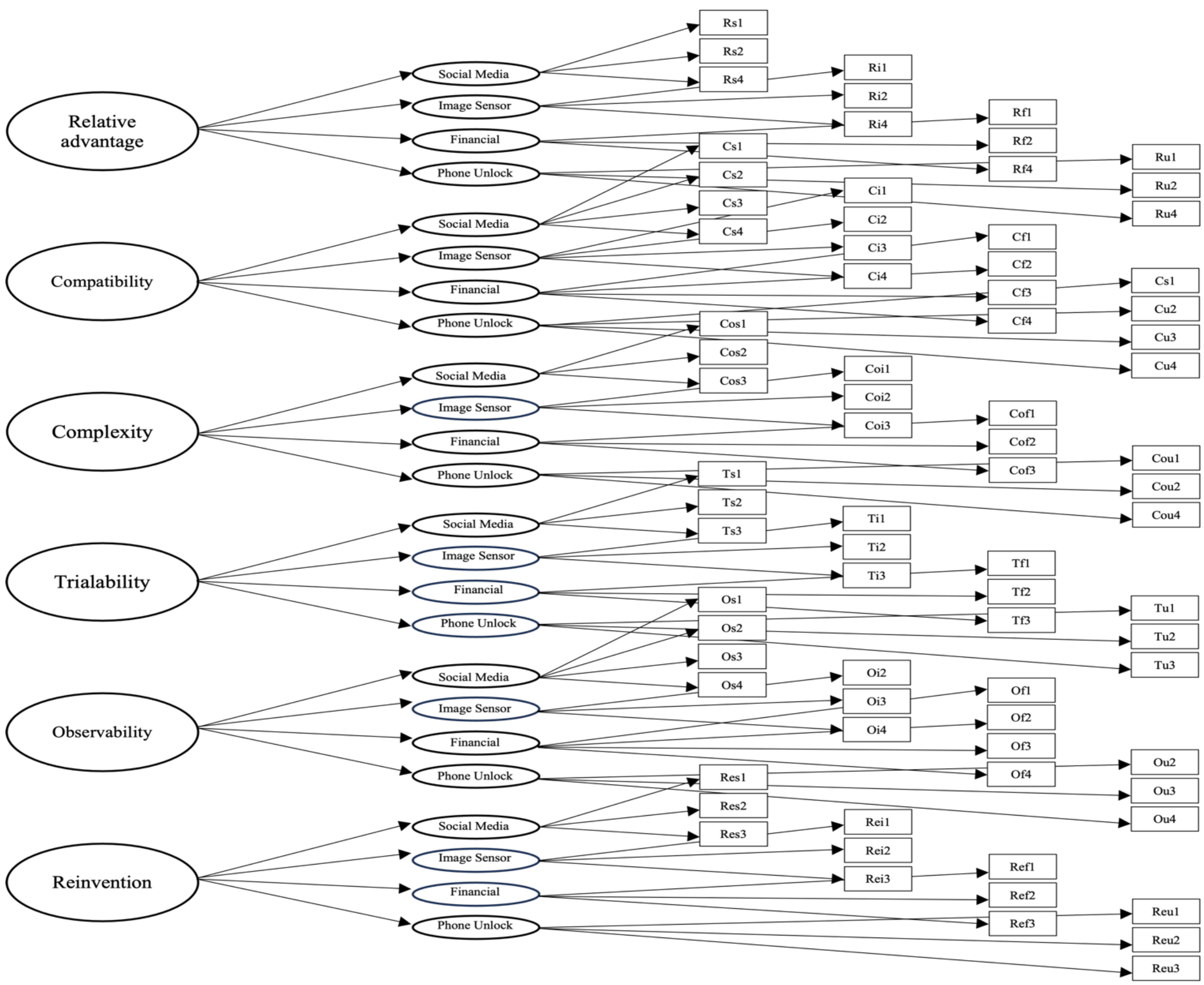
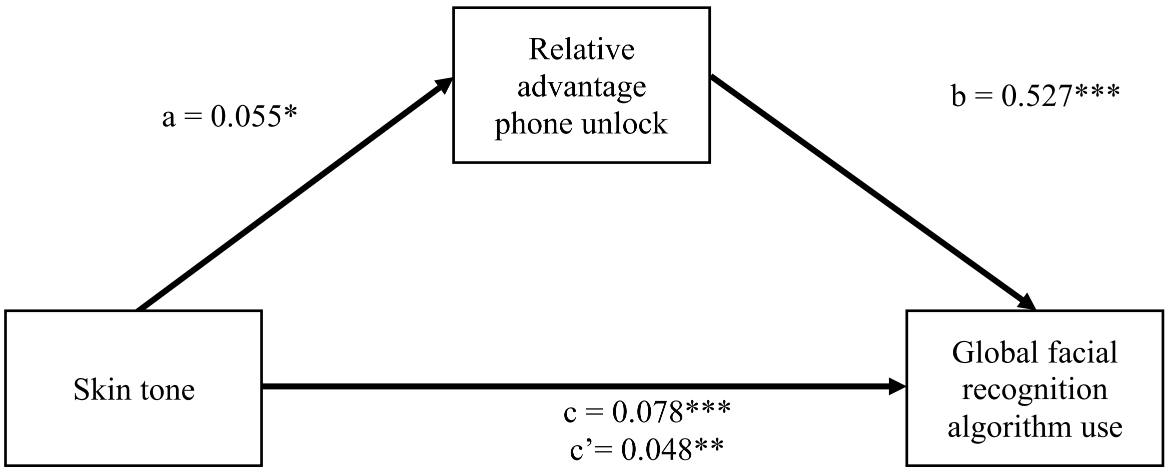


Figure 2

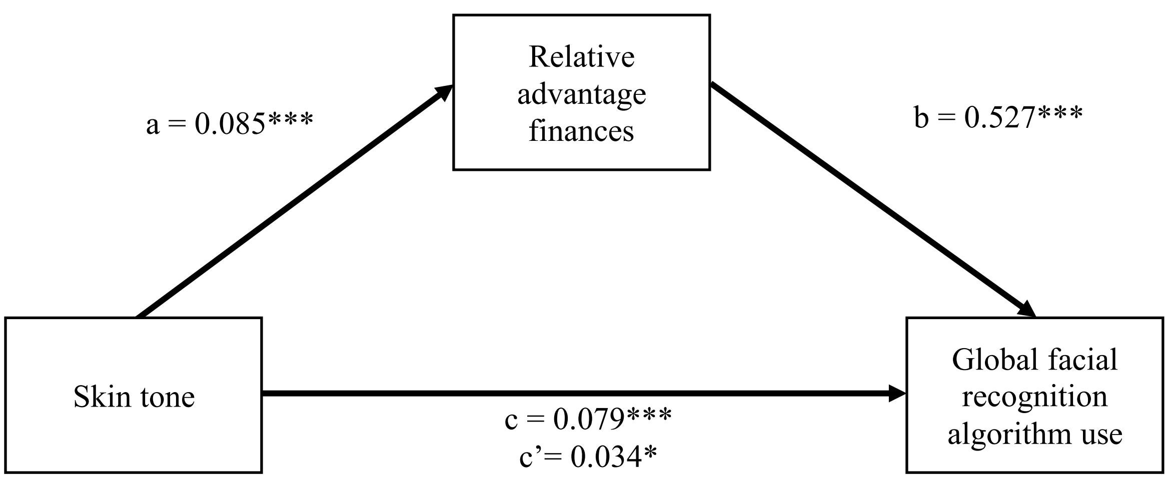
Relative Advantage Phone Unlock: H1 Mediation Analysis Summary for Phone Unlock, DV Global Facial Recognition Algorithm use, No Covariates



**p < .05, ** p < .01, *** p < .001*

Figure 3

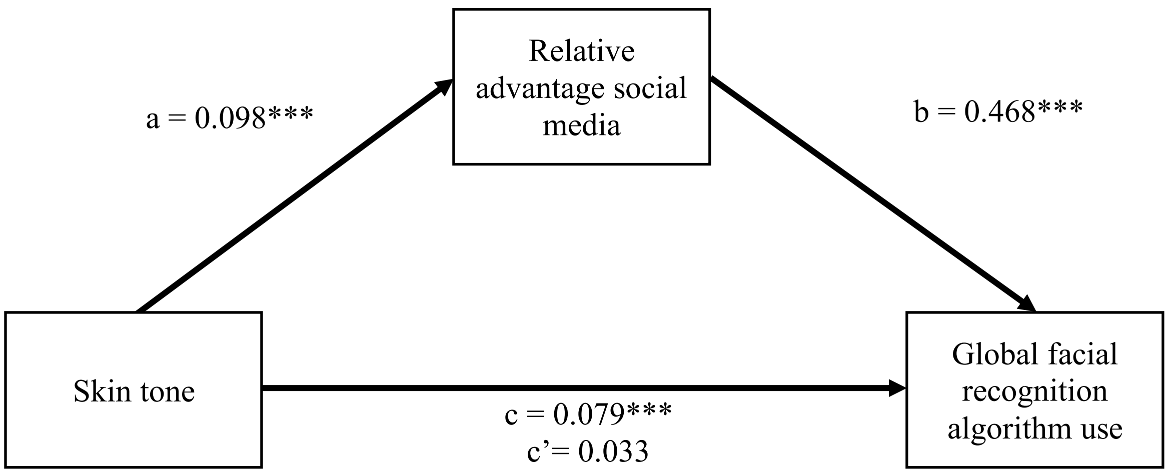
Relative Advantage Finances: H1 Mediation Analysis Summary for Finances, DV Global Facial Recognition Algorithm Use, No Covariates



**p < .05, ** p < .01, *** p < .001*

Figure 4

Relative Advantage Social Media: H1 Mediation Analysis Summary for Social Media, DV Global Facial Recognition Algorithm Use, No Covariates



**p < .05, ** p < .01, *** p < .001*

Figure 5

Relative Advantage Image Sensors: H1 Mediation Analysis Summary for Image Sensors, DV Global Image Sensor Algorithm Use, No Covariates

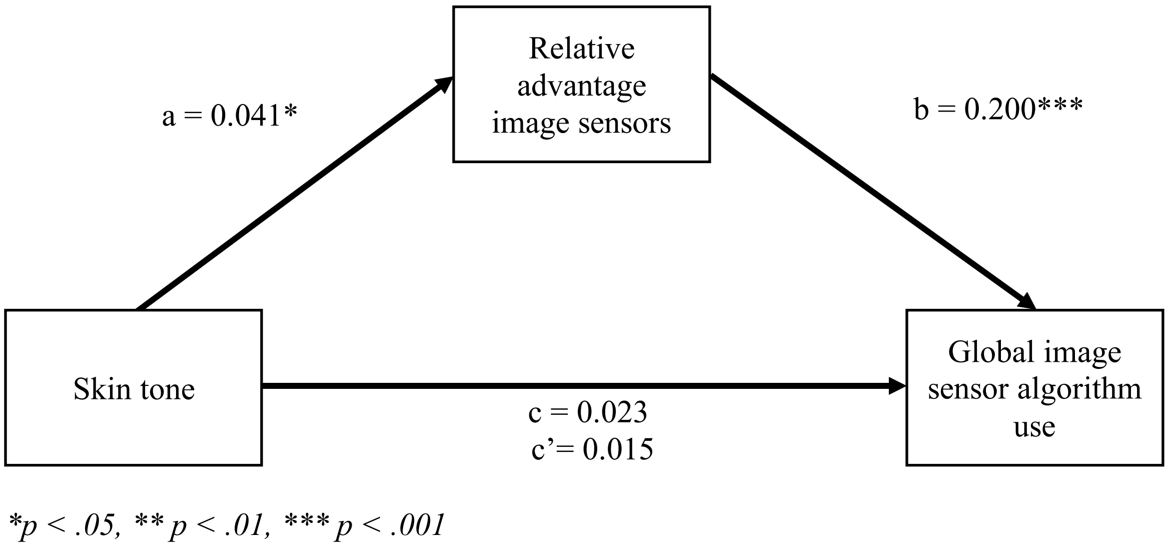


Figure 6

Compatibility: H2 Mediation Analysis Summary for Phone Unlock, DV Global Facial Recognition Algorithm Use, No Covariates

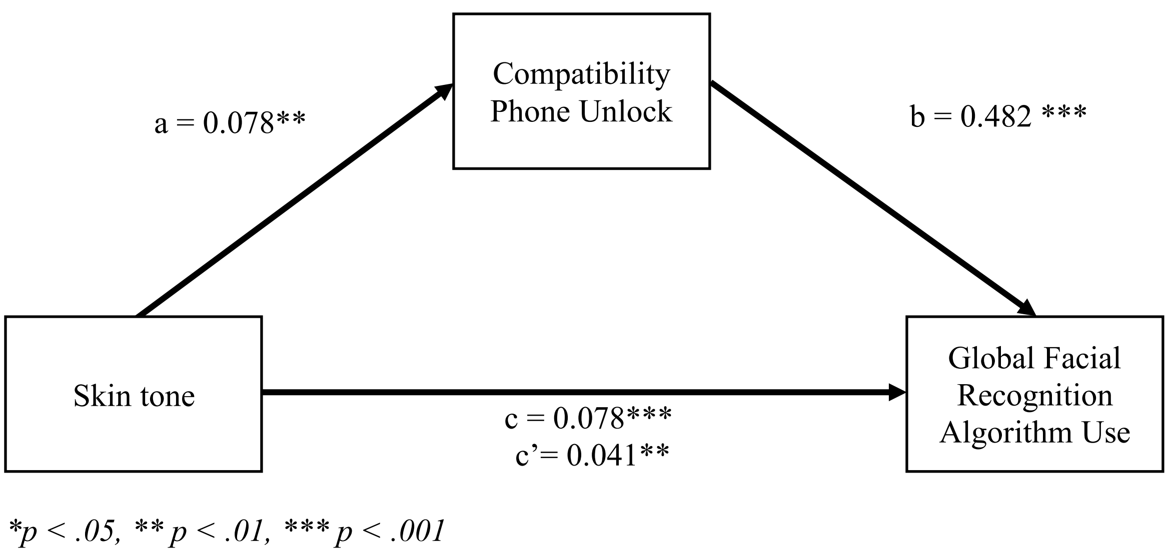
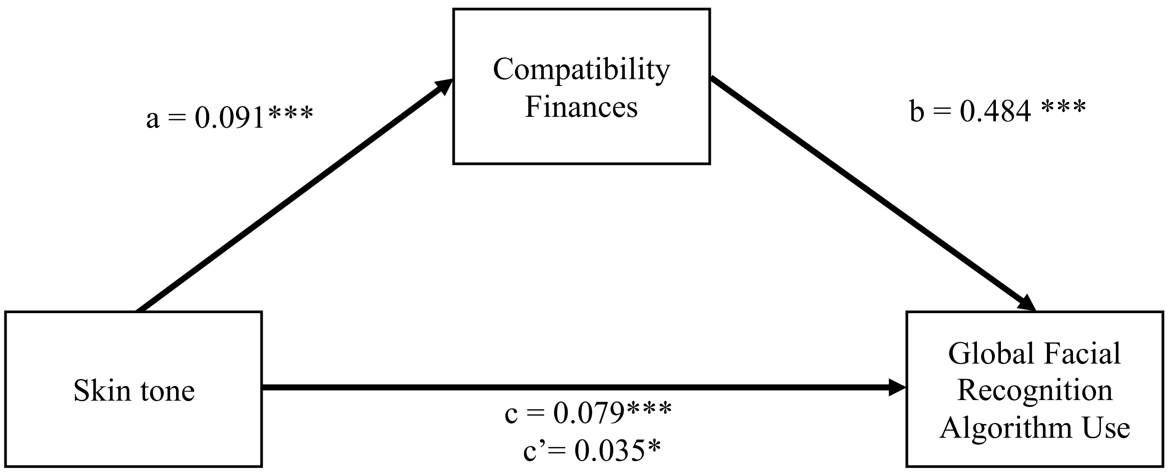


Figure 7

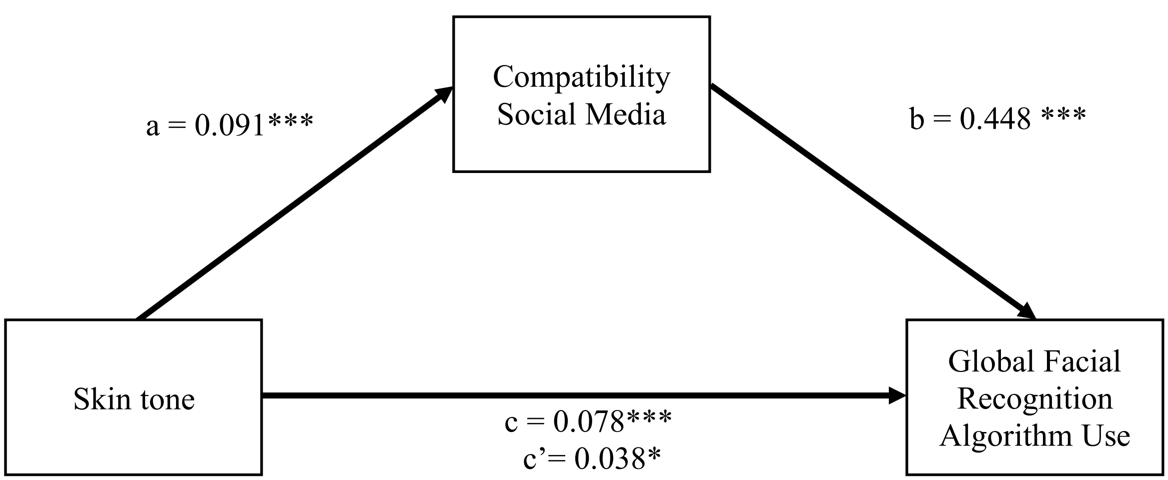
Compatibility Finances: H2 Mediation Analysis Summary for Finances, DV Global Facial Recognition Algoirthm Use, No Covariates



**p < .05, ** p < .01, *** p < .001*

Figure 8

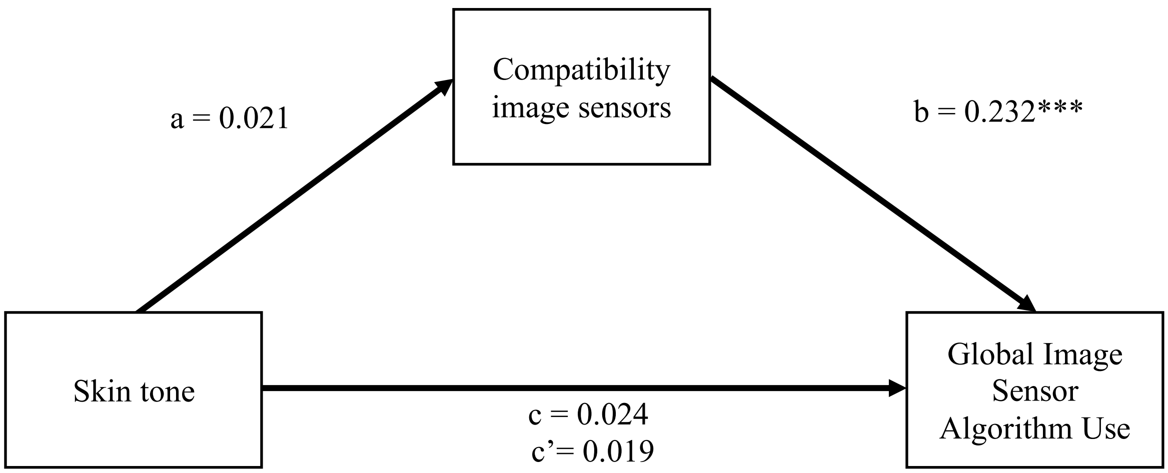
Compatibility Social Media: H2 Mediation Analysis Summary for Social Media, DV Global Facial Recognition Algorithm Use, No Covariates



*$p < .05$, ** $p < .01$, *** $p < .001$*

Figure 9

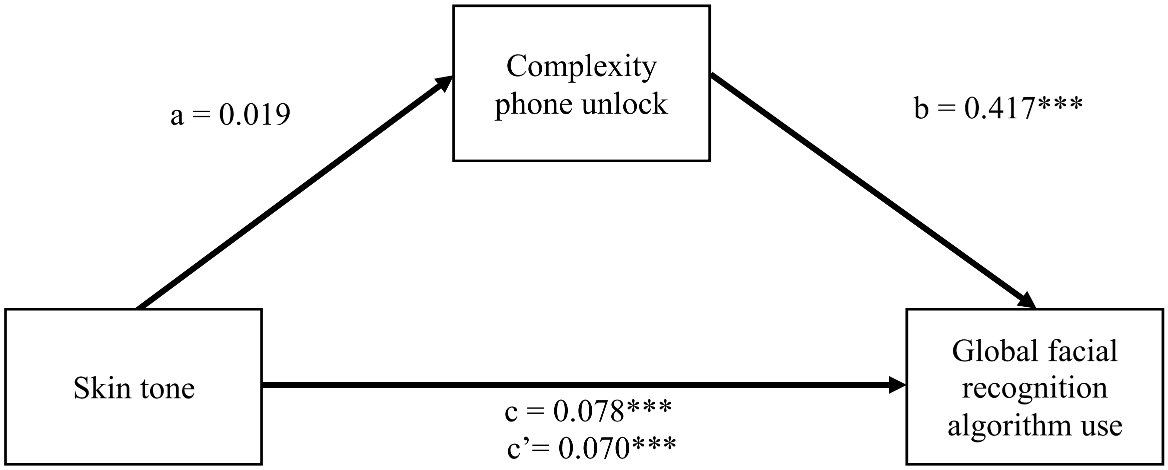
Compatibility Image Sensors: H2 Mediation Analysis Summary for Image Sensors, DV Global Image Sensor Algorithm Use, No Covariates



*$p < .05$, ** $p < .01$, *** $p < .001$*

Figure 10

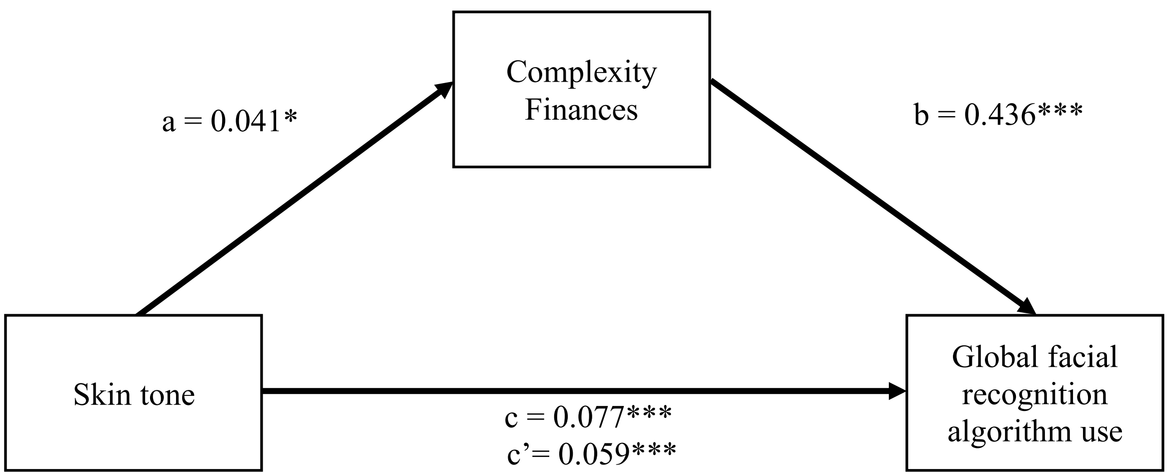
Complexity Phone Unlock: H3 Mediation Analysis Summary for Phone Unlock, DV Global Facial Recognition Algorithm Use, No Covariates



**p < .05, ** p < .01, *** p < .001*

Figure 11

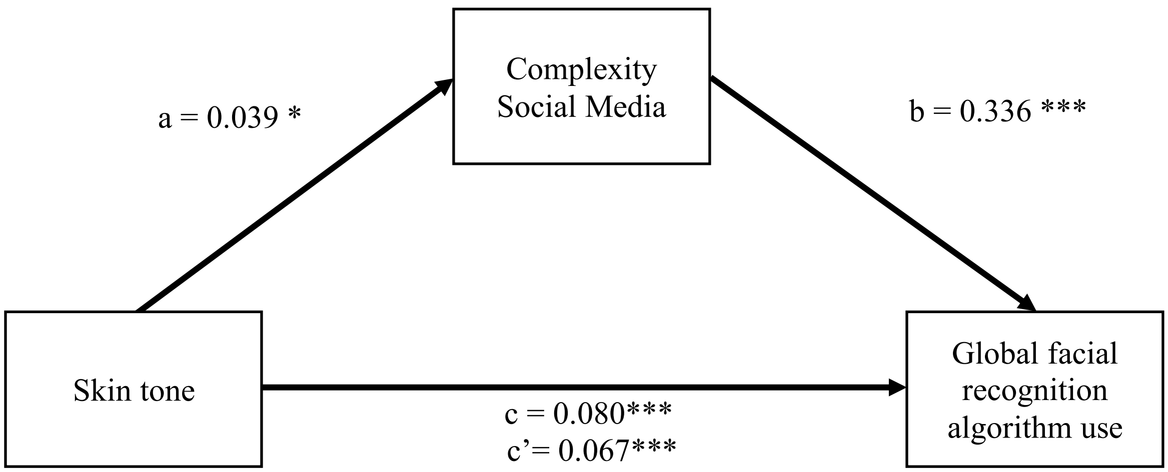
Complexity Finances: H3 Mediation Analysis Summary for Finances, DV Global Facial Recognition Algorithm Use, No Covariates



**p < .05, ** p < .01, *** p < .001*

Figure 12

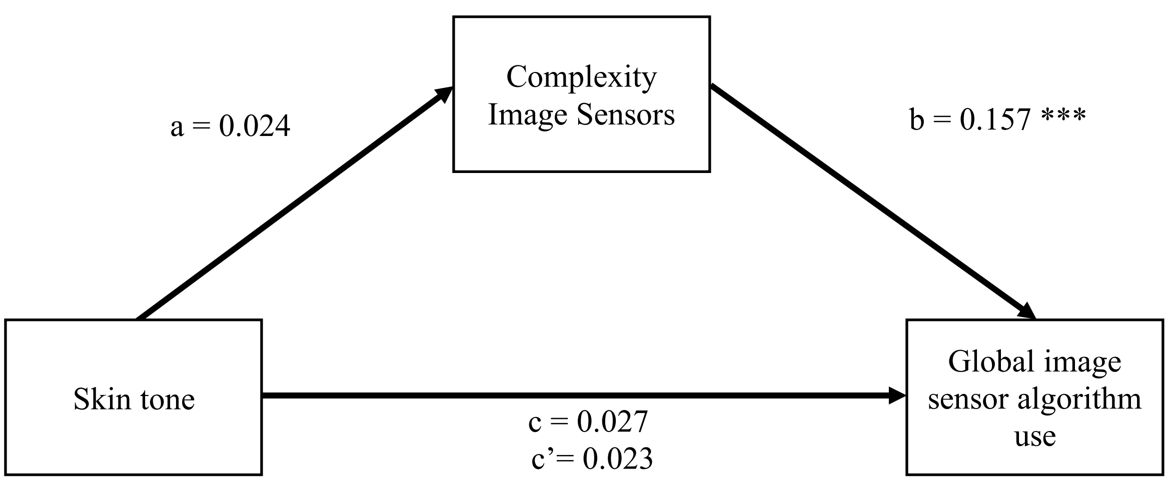
Complexity Social Media: H3 Mediation Analysis Summary for Social Media, DV Global Facial Recognition Algorithm Use, No Covariates



p* < .05, ** *p* < .01, * *p* < .001*

Figure 13

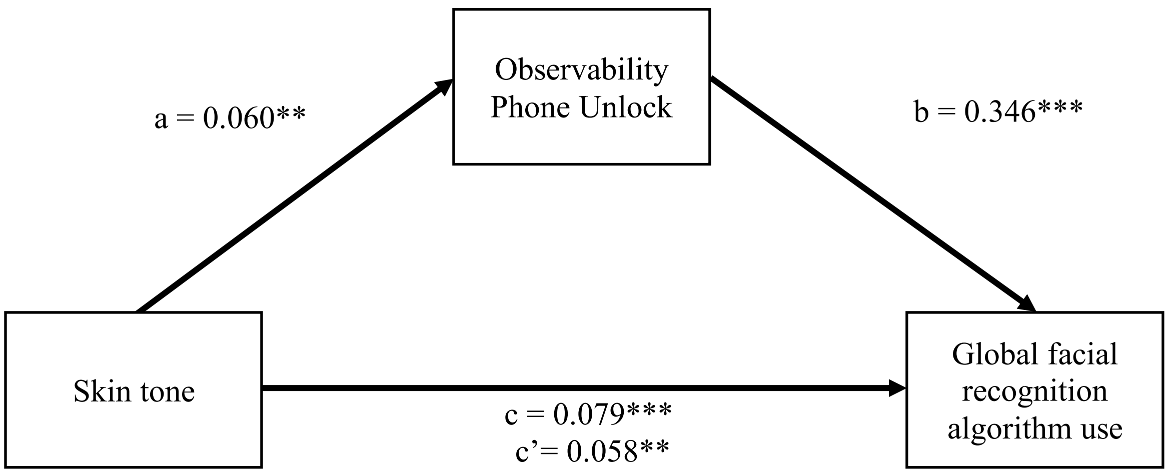
Complexity Image Sensors: H3 Mediation Analysis Summary for Image Sensors, DV Global Image Sensor Algorithm Use, No Covariates



**p < .05, ** p < .01, *** p < .001*

Figure 14

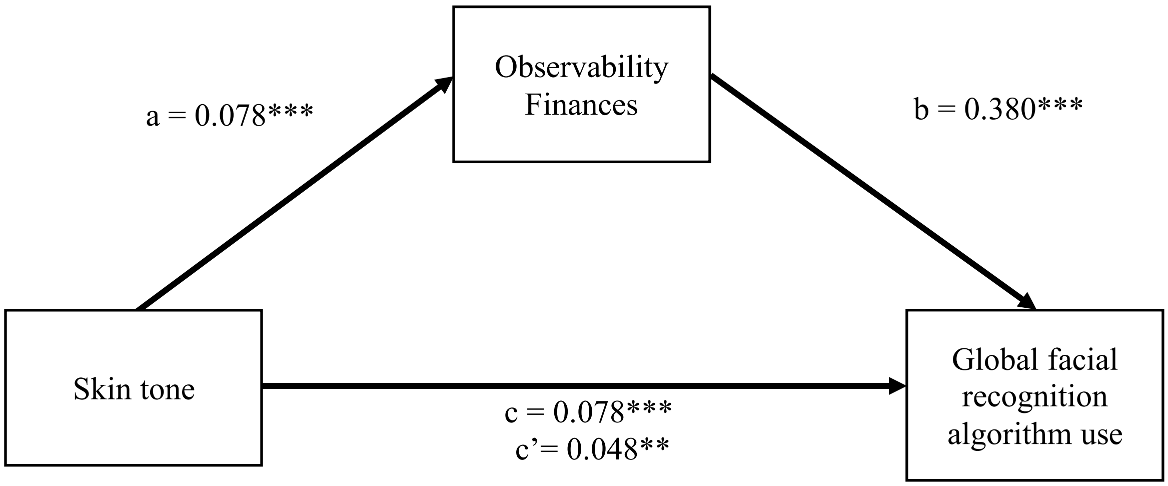
Observability Phone Unlock: H4 Mediation Analysis Summary for Phone Unlock, DV Global Facial Recognition Algorithm Use, No Covariates



**p < .05, ** p < .01, *** p < .001*

Figure 15

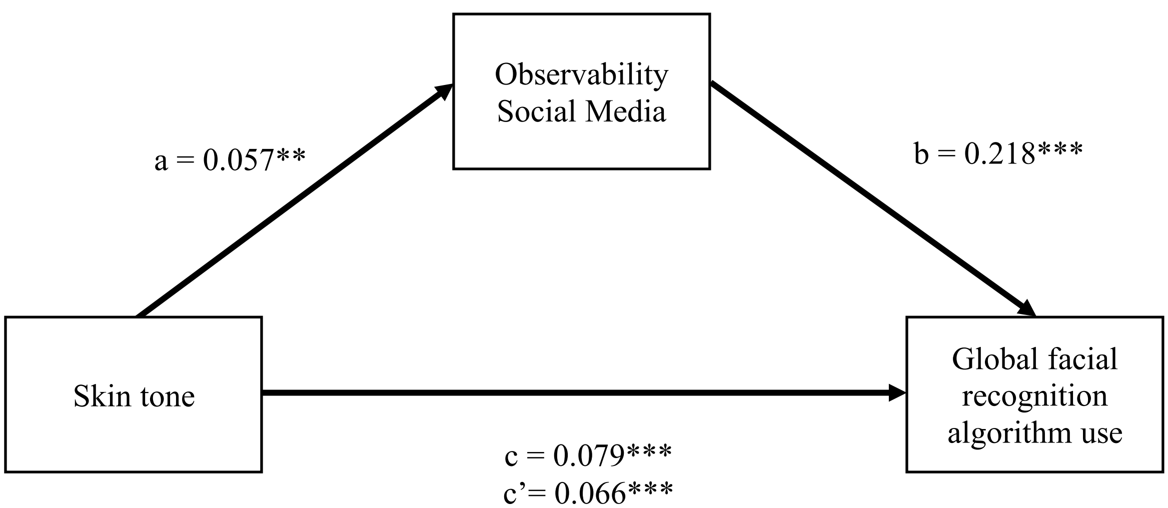
Observability Finances: H4 Mediation Analysis Summary for Finances, DV Global Facial Recognition Algorithm Use, No Covariates



**p < .05, ** p < .01, *** p < .001*

Figure 16

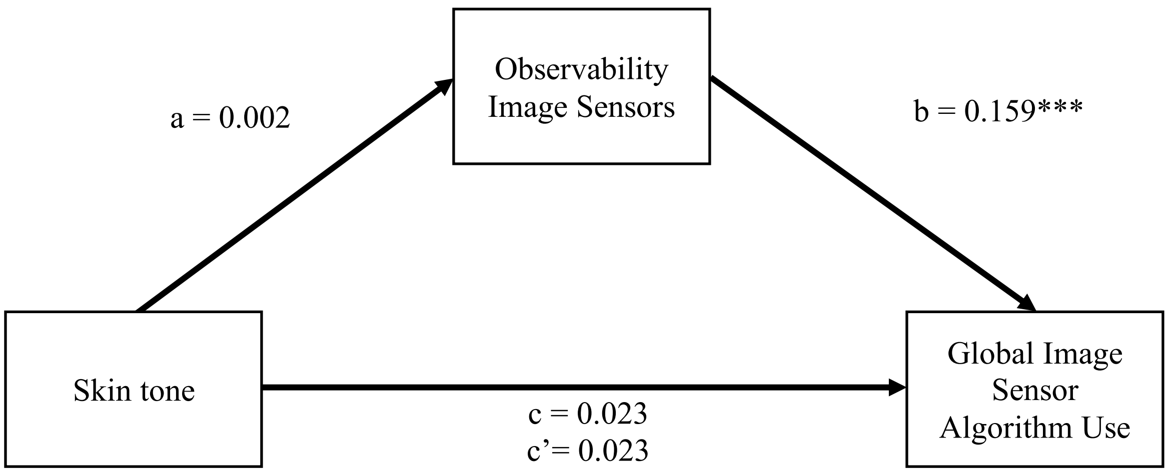
Observability Social Media: H4 Mediation Analysis Summary for Social Media, DV Global Facial Recognition Algorithm Use, No Covariates



**p < .05, ** p < .01, *** p < .001*

Figure 17

Observability Image Sensors: H4 Mediation Analysis Summary for Image Sensors, DV Global Image Sensor Algorithm Use, No Covariates



*p < .05, ** p < .01, *** p < .001

Figure 18

RQ2 Moderation Analysis: IV Skin Tone, DV Facial Recognition Technology Use, Moderator Algorithm Knowledge Facial Recognition Algorithms

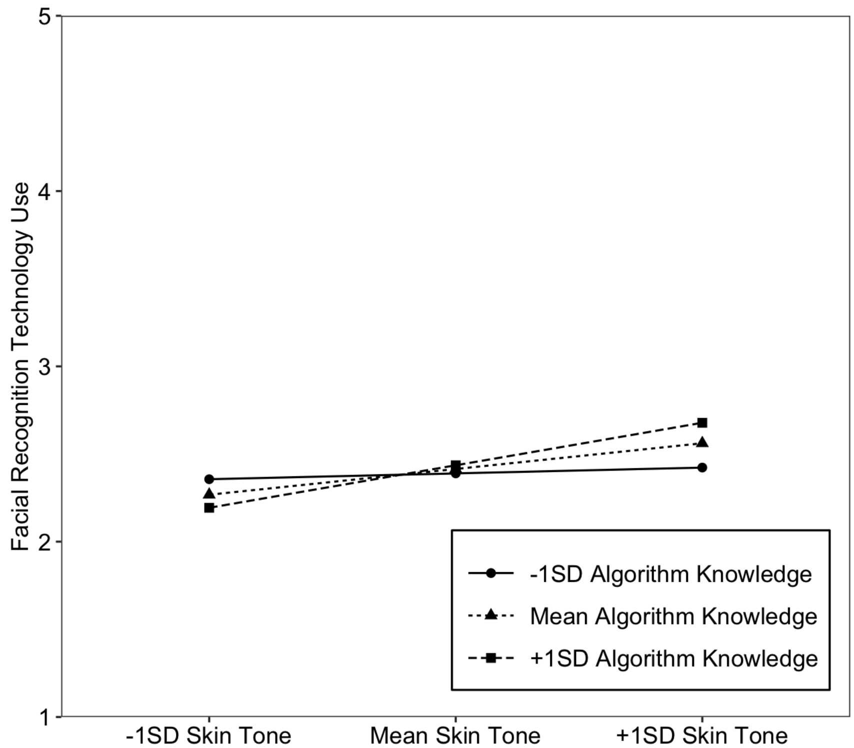
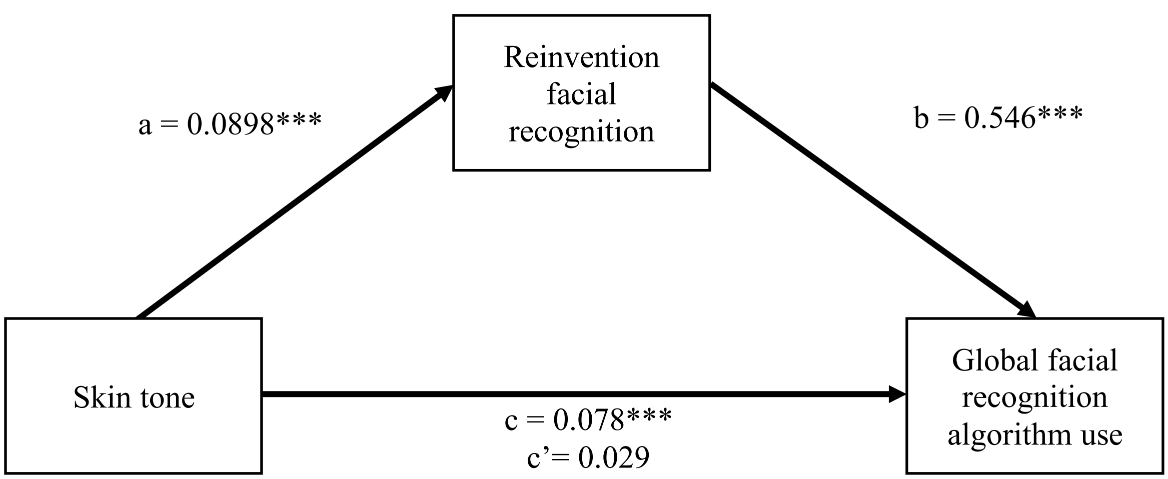


Figure 19

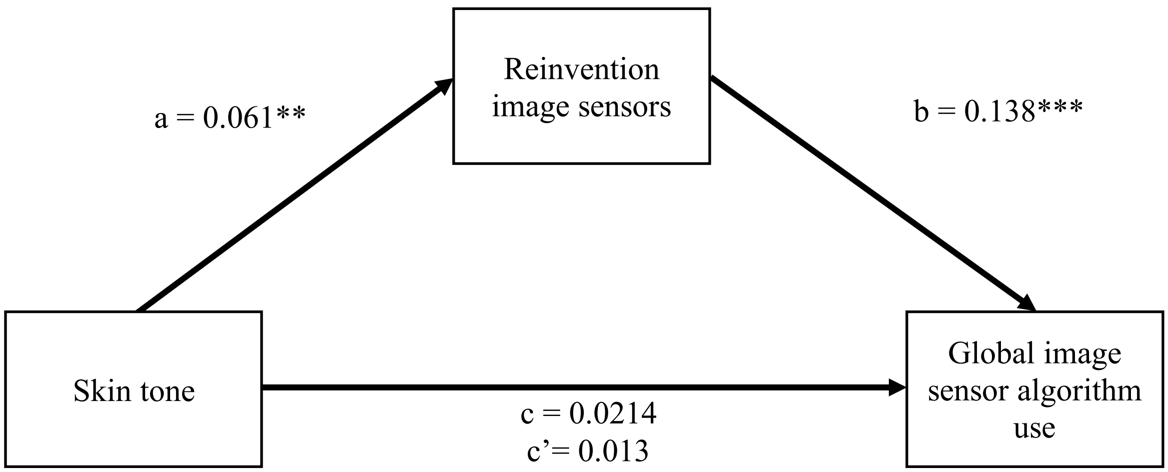
Reinvention Facial Recognition Algorithms: Exploratory Mediation Analysis Summary for Reinvention, DV Global Facial Recognition Algorithm Use, No Covariates



*p < .05, ** p < .01, *** p < .001

Figure 20

Reinvention Image Sensors: H4 Mediation Analysis Summary for Reinvention, DV Global Image Sensor Algorithm Use, No Covariates



*p < .05, ** p < .01, *** p < .001

Appendix A: Measures

Table 17

Relative Advantage Final Questions

	Phone Unlock	Financial	Social Media	Image Sensors
R1	Facial recognition technology allows me to accomplish tasks, such as unlocking my phone, more efficiently	Facial recognition technology allows me to accomplish tasks, such as checking my bank account, more efficiently	Facial filters allow me to accomplish tasks such as participating in trends on social media more efficiently	Image sensors allow me to complete my tasks more quickly
R2	Facial recognition is the best way to unlock my phone	Facial recognition is the best way to access a bank account	Facial filters are the best way to participate on social media	Image sensors are the best way to complete tasks

R4	Using facial recognition technology helps me unlock my phone better than not using facial recognition	Using facial recognition technology helps me accomplish tasks, such as checking my bank account, better than not using facial recognition	Facial filters help me accomplish tasks on social media such as participating in trends better than not using facial recognition	Using image sensors help me accomplish tasks better than not using image sensors

Table 18

Compatibility Final Questions

	Phone Unlock	Financial	Social Media	Image Sensors
C1	Facial recognition technology fits well with the way that I like to use my phone	Facial recognition technology fits well with the way that I like to use technology to check my financial accounts	Facial filters fit well with the way that I like to use social media	Using image sensors fits well with the way that I like to use technology
C2	Facial recognition technology is completely compatible with my current way of using my phone	Facial recognition technology is completely compatible with my current way of using technology to check my financial accounts	Facial filters are completely compatible with my current way of using social media	Using image sensors is completely compatible with my current way of using technology
C3	Facial recognition technology suits my needs when unlocking my phone	Facial recognition technology suits my needs when accessing my financial accounts	Facial filters suit my needs when using social media	Using image sensors suits my needs
C4	Facial recognition technology integrates well with my current way of using my phone	Facial recognition technology integrates well with my current way of using technology to check my financial accounts	Facial filters integrate well with my current way of using social media	Using image sensors integrates well with my current way of using technology

Table 19

Complexity Final Questions

	Phone Unlock	Financial	Social Media	Image Sensors
CO1	It is easy to get facial recognition algorithms to do what I want them to do when using them to unlock a phone	It is easy to get facial recognition algorithms to do what I want them to do when checking my financial accounts	It is easy to get facial recognition algorithms on social media to do what I want them to do	It is easy to get image sensors to do what I want them to do
CO2	Learning to operate facial recognition technology to unlock a phone is easy for me	Learning to operate facial recognition technology to access my financial accounts is easy for me	Learning to operate facial recognition technology on social media is easy for me	Learning to operate image sensing technology is easy for me
CO3	My interaction with facial recognition technology used to unlock a phone is clear and understandable	My interaction with facial recognition technology to access my financial is clear and understandable	My interaction with facial recognition technology on social media is clear and understandable	My interaction with image sensing technology is clear and understandable

Table 20

Trialability Final Questions

	Phone Unlock	Financial	Social Media	Image Sensors
T1	I have the ability to try out facial recognition technology to unlock a phone before deciding whether I like it or not	I have the ability to try out facial recognition technology to check my financial accounts before deciding whether I like it or not	I have the ability to try out facial recognition technology on social media before deciding whether I like it or not	I have the ability to try out image sensors before deciding whether I like them or not
T2	Trying facial recognition to unlock a phone	Trying facial recognition technology to	Trying facial recognition algorithms on	Trying image sensing technology has

	has informed my decision to use facial recognition to unlock a phone	check my financial accounts has informed my decision to use facial recognition algorithms	social media has informed my decision to use facial recognition algorithms	informed my decision to use image sensing technology
T3	I have had the opportunity to try facial recognition to unlock a phone in the past	I have had the opportunity to try facial recognition to check my financial accounts in the past	I have had the opportunity to try facial recognition algorithms on social media in the past	I have had the opportunity to try image sensing technology in the past

Table 21

Observability Final Questions

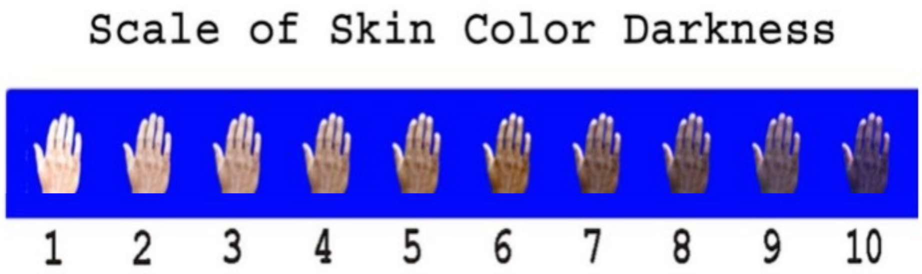
	Phone Unlock	Financial	Social Media	Image Sensors
O2	I am able to observe when others in my environment use facial recognition technology to unlock a phone	I am able to observe when others in my environment use facial recognition technology to check their financial accounts	I am able to observe when others in my environment use facial recognition technology such as social media facial filters	I am able to observe when others in my environment use image sensors to accomplish tasks such as washing their hands
O3	My friends are able to observe the results of using facial recognition technology to unlock a phone	My friends are able to observe the results of using facial recognition technology to check financial accounts	My friends are able to observe the results of using facial recognition technology such as social media facial filters	My friends are able to observe the results of using image sensors such as when they observe others using an automatic water faucet
O4	Others in my environment notice the impact of using facial recognition technology to unlock a phone	Others in my environment notice the impact of using facial recognition technology to check financial accounts	Others in my environment notice the impact of using facial recognition technology such as social media facial filters	Others in my environment notice the impact of using image sensors such as automatic water faucets

Table 22

Reinvention Finall Questions

	Phone Unlock	Financial	Social Media	Image Sensor
Re1	I often have to experiment with new ways of using facial recognition technology when using it to unlock my phone	I often have to experiment with new ways of using facial recognition technology	I often have to experiment with new ways of using facial recognition technology such as social media facial filters	I often have to experiment with new ways of using image sensing technology
Re2	I often have to modify facial recognition technology to get it to work for me when unlocking my phone	I often have to modify facial recognition technology to get it to work for me facial recognition algorithms	I often have to modify facial recognition technology such as social media facial filters to get it to work for me	I often have to modify image sensing technology to get it to work for me
Re3	I adapt facial recognition technology in a way that is different from how it was originally intended to be used when unlocking my phone	I adapt facial recognition technology in a way that is different from how it was originally intended to be used	I adapt facial recognition technology such as social media facial filters in a way that is different from how it was originally intended to be used	I have adapted image sensing technology in a way that is different from how it was originally intended to be used

Skin tone measure



Perceived skin tone bias in algorithms

Please indicate how much you agree with the following statements (1) *strongly disagree* (5) *strongly agree*

- Results delivered by AI algorithms tend to be slanted against my skin tone
- Most results from image recognition algorithms are distorted by skin tone bias in AI systems
- Bias in algorithms is harmful for people who have similar skin tones to me
- Your gender
- Your skin tone

In general how often do you use the following technologies (*never, rarely, sometimes, very often, always*)

- Automatic image tagger on social media
- Automatic water dispenser that detects hand movement, like those used by a sink

- Face ID to unlock your phone
- Face ID used to access a bank or other finical service.
- Google photos facial recognition for organizing photos
- Instagram facial filter
- Phone camera for a self-portrait or a picture of friends without a flash
- Snapchat facial filter
- TikTok facial filter
- Zoom facial filter

Algorithmic Knowledge

Generally speaking, how much INFLUENCE do you think the following factors have on the output of an image recognition algorithm (such as an automatic water dispensers or smart watches such as Apple Watch/Fitbit) (1 = *no influence*, 5 = *strong influence*)

- Distance and orientation of the objects from the sensor
- Lighting conditions of the environment
- Presence or absence of motion
- The training data used to develop the algorithm
- Your skin tone

In general how often do you use the following technologies (*never, rarely, sometimes, very often, always*)

- Apple Watch
- Automatic hand dryer
- Automatic paper towel dispenser

- Automatic soap dispenser
- Automatic water dispenser that detects hand movement, like those used by a sink
- Fitbit

Appendix B: Pre-Registered Analysis

Table 23

H1 Mediation Analysis Summary for Phone Unlock, DV Global Tech Use, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.082 (0.000)	0.052 (0.000)	0.036	0. 0041	0. 0565	Partial mediation
Technology use	0.043 (0.018)	0.033 (0.019)		-0.0134	0.0318	Non-significant
Technology use and income	0.047 (0.009)	0.036 (0.012)	0.011	-0.0118	0.0334	Non-significant

Note. All results are unstandardized effect sizes

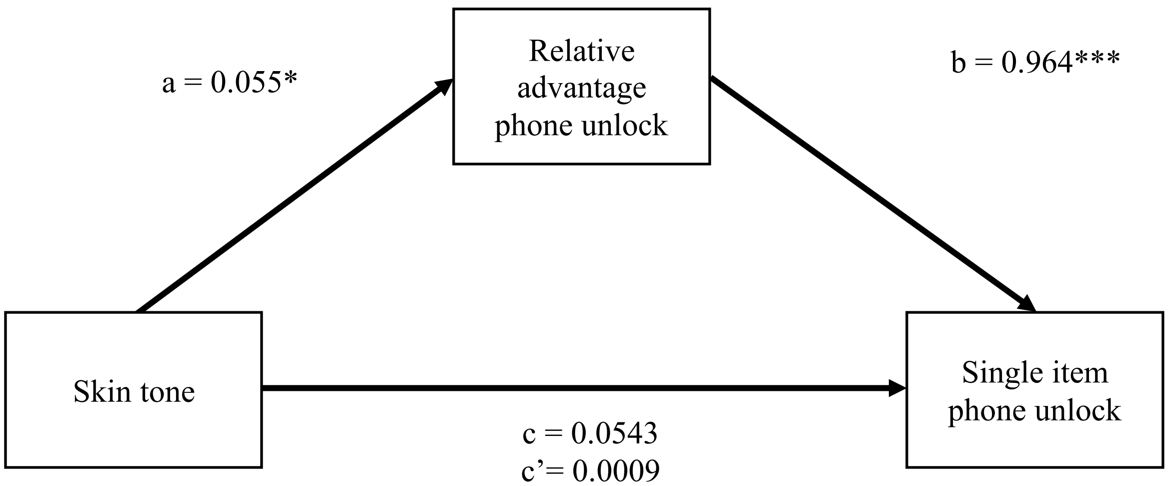
Table 24

H1 Mediation Analysis Summary for Phone Unlock, DV single item phone unlock, No Covariates

Relationship	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Skin tone -> RA phone unlock -> single item phone unlock	0.0543 (0.084)	0.0009 (0.96)	0.0533	0.0039	0.0992	Mediation?

Figure 21

Relative Advantage Phone Unlock: H1Mediation Analysis Summary for Phone Unlock, DV Single Item Phone Unlock, No Covariates



p* < .05, ** *p* < .01, * *p* < .001*

Table 25

H1 Mediation Analysis Summary for Phone Unlock, DV single item phone unlock, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.060 (0.052)	0.004 (0.859)	0.057	0. 0096	0. 1044	Mediation?
Technology use	0.013 (0.655)	-0.005 (0.797)	0.019	-0.0278	0.0638	Non-significant
Technology use and income	0.020 (0.508)	-0.003 (0.894)	0.023	-0.0245	0.0682	Non-significant

Note. All results are unstandardized effect sizes

Table 26

H1 Mediation Analysis Summary for Finances, DV Global Tech Use, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.083 (0.000)	0.037 (0.012)	0.046	0.0196	0.0717	Partial mediation
Technology use	0.045 (0.012)	0.019 (0.181)	0.026	0.0022	0.0483	Mediation
Technology use and income	0.049 (0.006)	0.021 (0.139)	0.0284	0.0116	0.0062	Mediation

Note. All results are unstandardized effect sizes

Table 27

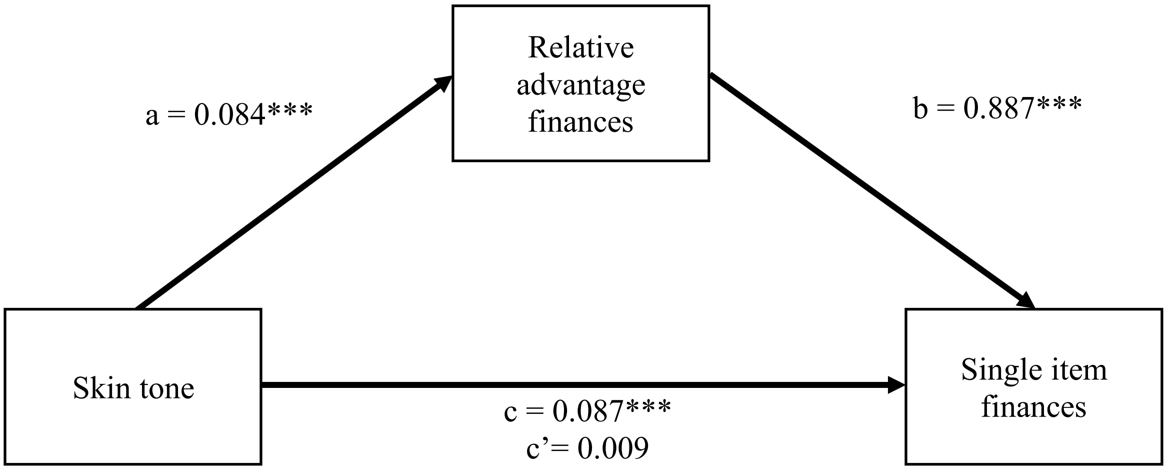
H 1Mediation Analysis Summary for Finances, DV Single Item Finances, No Covariates

Relationship	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Skin tone -> RA phone unlock -> single item finances	0.087 (0.003)	0.009 (0.655)	0.078	0.0339	0.1219	Mediation

Note. All results are unstandardized effect sizes

Figure 22

Relative Advantage Finances: H1 Mediation Analysis Summary for Finances, DV Single Item Finances, No Covariates



**p < .05, ** p < .01, *** p < .001*

Table 28

Relative Advantage Finances: H1 Mediation Analysis Summary for Finances, DV Singles Item Finances, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.093 (0.002)	0.012 (0.567)	0.0814	0.0369	0.1238	Mediation
Technology use	0.048 (0.109)	-0.002 (0.908)	0.0499	0.0055	0.0921	Mediation
Technology use and income	0.054 (0.061)	-0.000 (0.996)	0.0544	0.0215	0.0128	Mediation

Note. All results are unstandardized effect sizes

Table 29

Relative Advantage Social Media: H1 Mediation Analysis Summary for Social Media, DV Global Facial Recognition Use, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval	Conclusion

				Lower bound	Upper bound	
Income	0.083 (0.000)	0.038 (0.023)	0.0459	0.0257	0.0668	Partial Mediation
Technology use	0.045 (0.012)	0.018 (0.271)	0.0276	0.0117	0.0450	Mediation
Technology use and income	0.050 (0.006)	0.022 (0.1734)	0.0282	0.0118	0.0453	Mediation

Note. All results are unstandardized effect sizes

Table 30

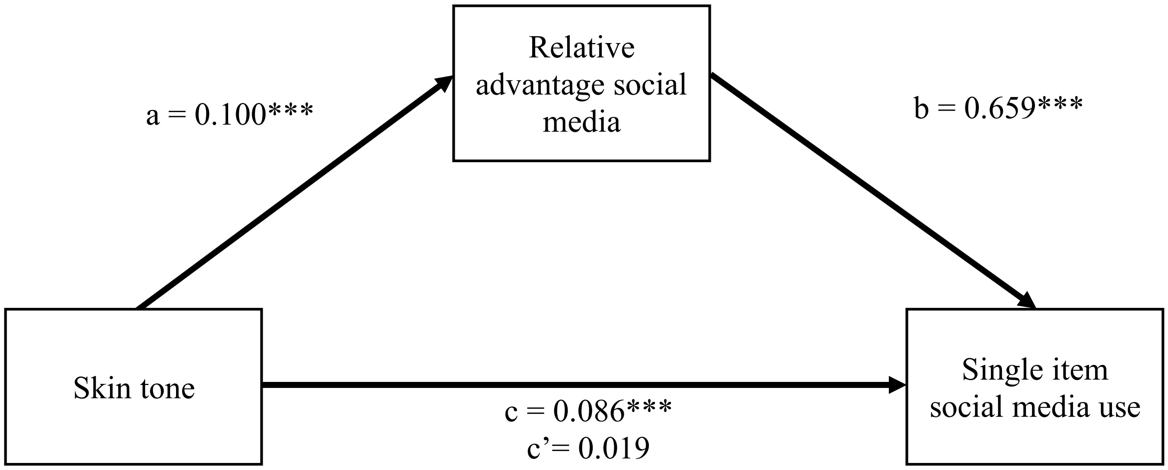
H1 Mediation Analysis Summary for Social Media, DV Single Item Social Media, No Covariates

Relationship	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Skin tone -> RA social media -> single item social media use	0.086 (0.000)	0.019 (0.311)	0.0663	0.0384	0.0949	Mediation

Note. All results are unstandardized effect sizes

Figure 23

Relative Advantage Finances: H1 Mediation Analysis Summary for Social Media, DV Single Item Social Media Use, No Covariates



**p < .05, ** p < .01, *** p < .001*

Table 31

Relative Advantage Social Media: H1 Mediation Analysis Summary for Social Media, DV Single Item Social Media Use, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.088 (0.000)	0.0200 (0.303)	0.0446	0.0395	0.0967	Mediation
Technology use	0.057 (0.015)	0.012 (0.530)	0.0276	0.0188	0.0705	Mediation
Technology use and income	0.057 (0.014)	0.011 (0.555)	0.0458	0.0202	0.0723	Mediation

Note. All results are unstandardized effect sizes

Table 25

Relative Advantage Image Sensors: H1 Mediation Analysis Summary for Image Sensors, DV Global Image Sensor Use, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval	Conclusion

				Lower bound	Upper bound	
Income	0.026 (0.076)	0.018 (0.208)	0.008	-0.0001	0.0172	Non-significant
Technology use	-0.012 (0.371)	-0.014 (0.291)	0.002	-0.0030	0.0071	Non-significant
Technology use and income	-0.009 (0.489)	-0.012 (0.386)	0.002	-0.0028	0.0075	Non-significant

Note. All results are unstandardized effect sizes

Table 32

Compatibility Phone Unlock: H2 Mediation Analysis Summary for Phone Unlock, DV Global Facial Recognition Technology Use, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.082 (0.000)	0.044 (0.003)	0.0382	0.0134	0.0632	Partial Mediation
Technology use	0.045 (0.013)	0.026 (0.069)	0.0184	-0.0039	0.0399	Non-significant
Technology use and income	0.049 (0.006)	0.030 (0.041)	0.0194	-0.0026	0.0411	Non-significant

Note. All results are unstandardized effect sizes

Table 33

H2 Mediation Analysis Summary for Phone Unlock, DV single item phone unlock, No Covariates

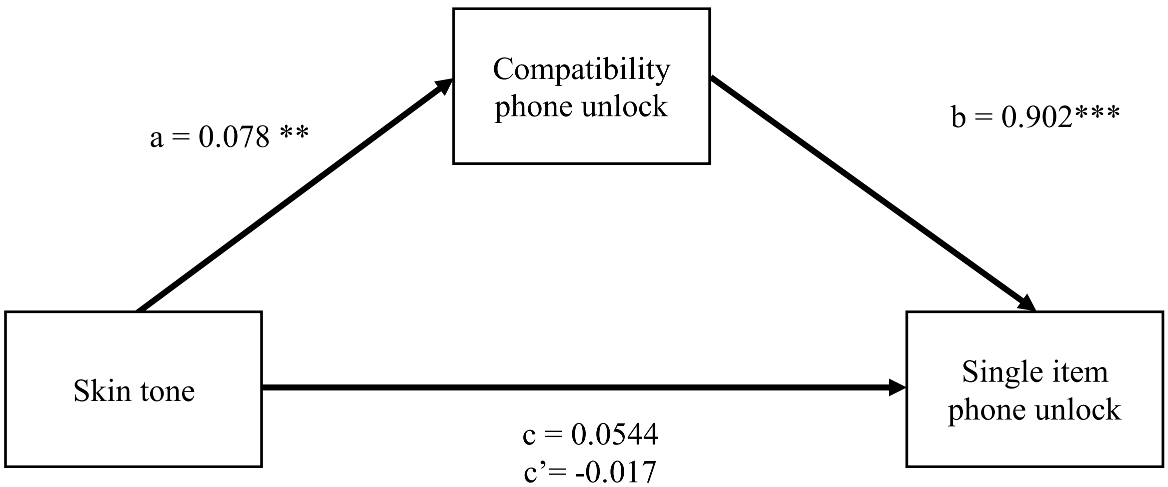
Relationship	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Skin tone -> Compatibility phone	0.0544 (0.083)	-0.017 (0.42)	0.0710	0.0240	0.1188	Mediation?

unlock -> single item phone unlock	

Note. All results are unstandardized effect sizes

Figure 24

Compatibility Phone Unlock: H2 Mediation Analysis Summary for Phone Unlock, DV Single Item Phone Unlock, No Covariates



p* < .05, ** *p* < .01, * *p* < .001

Table 34

H2 Mediation Analysis Summary for Phone Unlock, DV single item phone unlock, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.060 (0.053)	-0.013 (0.525)	0.057	0.0247	0.1196	Mediation?

Technology use	0.016 (0.590)	-0.022 (0.284)	0.019	-0.0278	0.0638	Not significant
Technology use and income	0.020 (0.508)	-0.003 (0.894)	0.023	-0.0071	0.0840	Not significant

Note. All results are unstandardized effect sizes

Table 35

H2 Mediation Analysis Summary for Finances DV Global Facial Recognition Technology Use, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.0827 (0.000)	0.0377 (0.011)	0.045	0.0186	0.0702	Mediation
Technology use	0.046 (0.011)	0.019 (0.169)	0.026	0.004	0.049	Mediation
Technology use and income	0.0502 (0.005)	0.0217 (0.125)	0.0285	0.0059	0.0506	Mediation

Note. All results are unstandardized effect sizes

Table 36

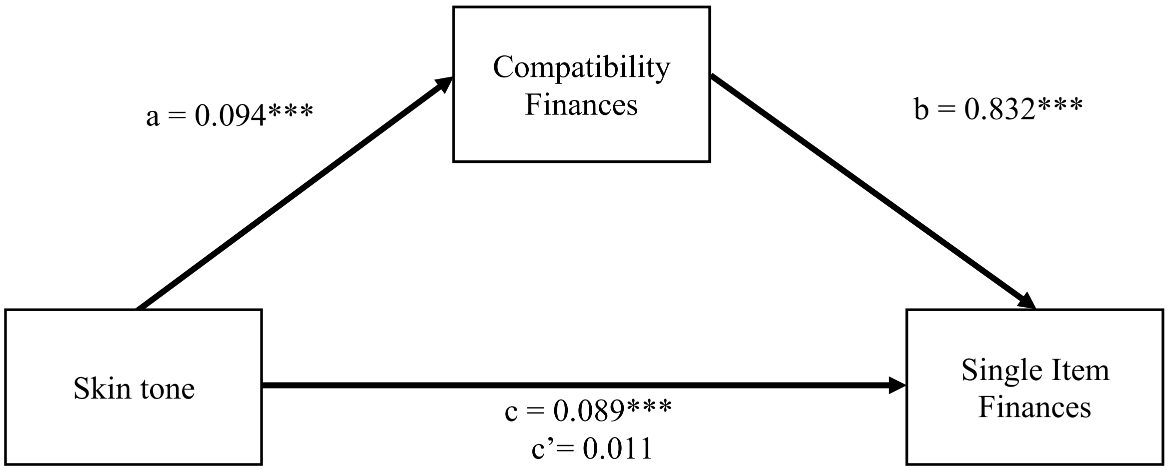
H2 Mediation Analysis Summary for Finances DV Single Item Finances, No Covariates

Relationship	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Skin tone -> Compatibility finances -> Single item finances	0.089 (0.003)	0.011 (0.5706)	0.078	0.034	0.1219	Mediation

Note. All results are unstandardized effect sizes

Figure 25

Compatibility Finances: H2 Mediation Analysis Summary for Finances, DV Single Item Finances, No Covariates



p* < .05, ** *p* < .01, * *p* < .001*

Table 37

H2 Mediation Analysis Summary for Finances DV Single Item Finances, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.095 (0.001)	0.015 (0.468)	0.0808	0.0363	0.1234	Mediation
Technology use	0.0502 (0.084)	-0.000 (0.992)	0.0504	0.0078	0.0502	Mediation?
Technology use and income	0.0573 (0.048)	0.0025 (0.902)	0.0548	0.012	0.0953	Mediation

Note. All results are unstandardized effect sizes

Table 38

H2 Mediation Analysis Summary for Social Media DV Global Facial Recognition Technology Use, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.083 (0.000)	0.042 (0.008)	0.0403	0.0191	0.0623	Mediation
Technology use	0.043 (0.016)	0.022 (0.157)	0.021	0.003	0.0391	Mediation
Technology use and income	0.048 (0.008)	0.027 (0.089)	0.0214	0.0034	0.04	Mediation

Note. All results are unstandardized effect sizes

Table 39

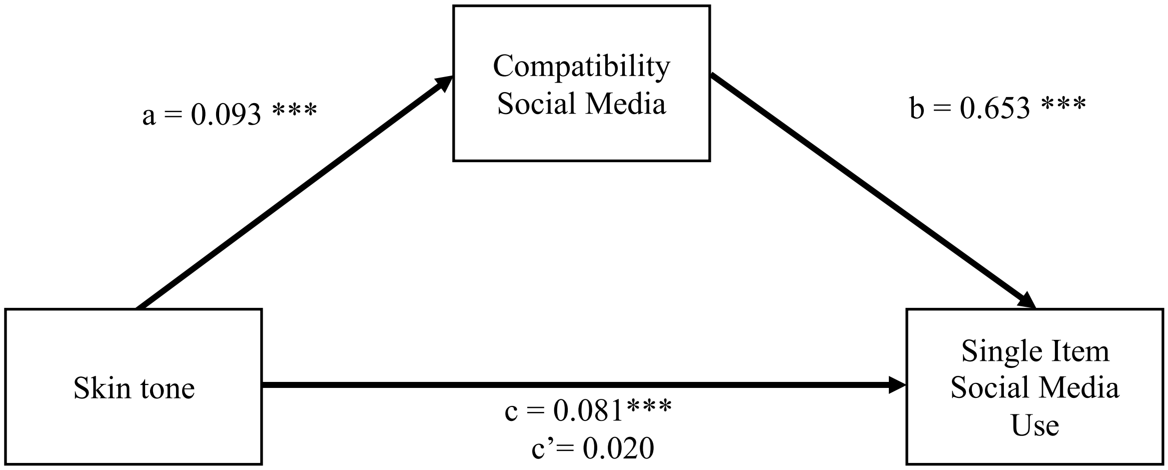
H2 Mediation Analysis Summary for Social Media DV Single Item Social Media Use, No Covariates

Relationship	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Skin tone -> Compatibility social media -> Single item social media use	0.0811 (0.000)	0.0203 (0.256)	0.0607	0.0268	0.093	Mediation

Note. All results are unstandardized effect sizes

Figure 26

Compatibility Finances: H2 Mediation Analysis Summary for Social Media, DV Single Item Social Media Use, No Covariates



**p < .05, ** p < .01, *** p < .001*

Table 40

H2 Mediation Analysis Summary for Social Media, DV Single Item Social Media Use, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.083 (0.001)	0.021 (0.021)	0.0618	0.0293	0.0942	Mediation
Technology use	0.051 (0.028)	0.015 (0.402)	0.0359	0.006	0.066	Mediation
Technology use and income	0.052 (0.029)	0.015 (0.4101)	0.0366	0.007	0.067	Mediation

Note. All results are unstandardized effect sizes

Table 41

Compatibility Image Sensors: H2 Mediation Analysis Summary for Image Sensors, DV Global Image Sensor Use, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval	Conclusion

				Lower bound	Upper bound	
Income	0.027 (0.071)	0.022 (0.123)	0.0053	-0.0044	0.015	Non-significant
Technology use	-0.011 (0.409)	-0.011 (0.223)	-0.0006	-0.0079	0.0059	Non-significant
Technology use and income	-0.008 (0.542)	-0.008 (0.546)	-0.0003	-0.0074	0.006	Non-significant

Note. All results are unstandardized effect sizes

Table 42

Complexity Phone Unlock: H3 Mediation Analysis Summary for Phone Unlock, DV Global Facial Recognition Technology Use, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.082 (0.000)	0.074 (0.000)	0.0082	-0.0073	0.0236	Non-significant
Technology use	0.044 (0.015)	0.045 (0.045)	-0.001	-0.0137	0.0109	Non-significant
Technology use and income	0.0487 (0.007)	0.0496 (0.0037)	-0.0009	-0.0138	0.0113	Non-significant

Note. All results are unstandardized effect sizes

Table 43

H3 Complexity Mediation Analysis Summary for Phone Unlock, DV Single Item Phone Unlock, No Covariates

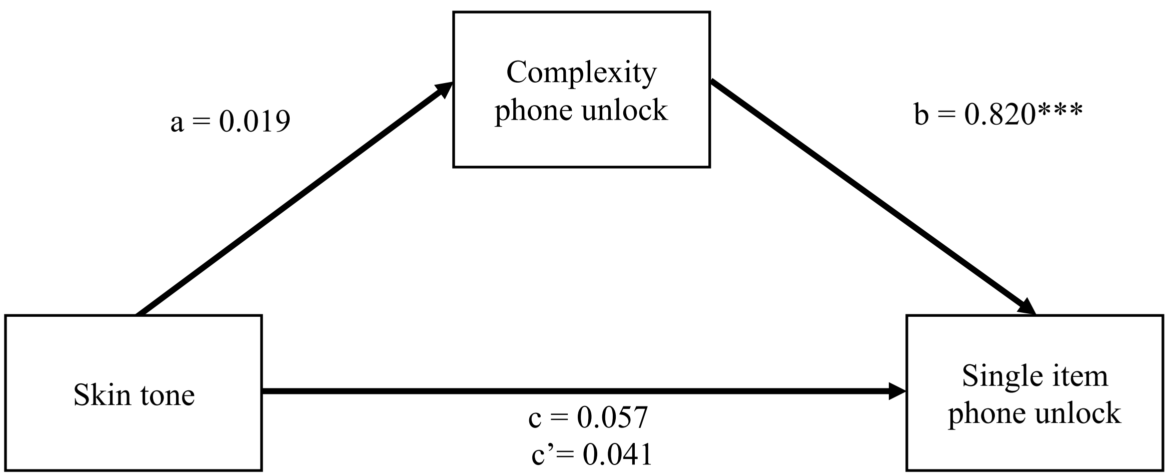
Relationship	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Skin tone -> Complexity phone	0.057 (0.070)	0.041 (0.233)	0.0157	-0.0152	0.045	Non-significant

unlock -> Single Item Phone Unlock						

Note. All results are unstandardized effect sizes

Figure 27

Complexity Phone Unlock: H3 Mediation Analysis Summary for Phone Unlock, DV Single Item Phone Unlock, No Covariates



p* < .05, ** *p* < .01, * *p* < .001

Table 44

Complexity Phone Unlock: H3 Mediation Analysis Summary for Phone Unlock, DV Single Item Phone Unlock, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.063 (0.044)	0.046 (0.091)	0.0164	-0.014	0.0448	Non-significant
Technology use	0.018 (0.553)	0.020 (0.457)	-0.0023	-0.0297	0.0246	Non-significant

Technology use and income	0.024 (0.422)	0.026 (0.332)	-0.002	-0.0301	0.0252	Non-significant

Note. All results are unstandardized effect sizes

Table 45

Complexity Finances: H3 Mediation Analysis Summary for Finances, DV Global Facial Recognition Technology Use, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.080 (0.000)	0.0620 (0.000)	0.0184	0.0013	0.0358	Mediation
Technology use	0.043 (0.018)	0.034 (0.036)	0.0085	-0.0078	0.0241	Non-significant
Technology use and income	0.047 (0.009)	0.0377 (0.021)	0.0095	-0.0063	0.025	Non-significant

Note. All results are unstandardized effect sizes

Table 46

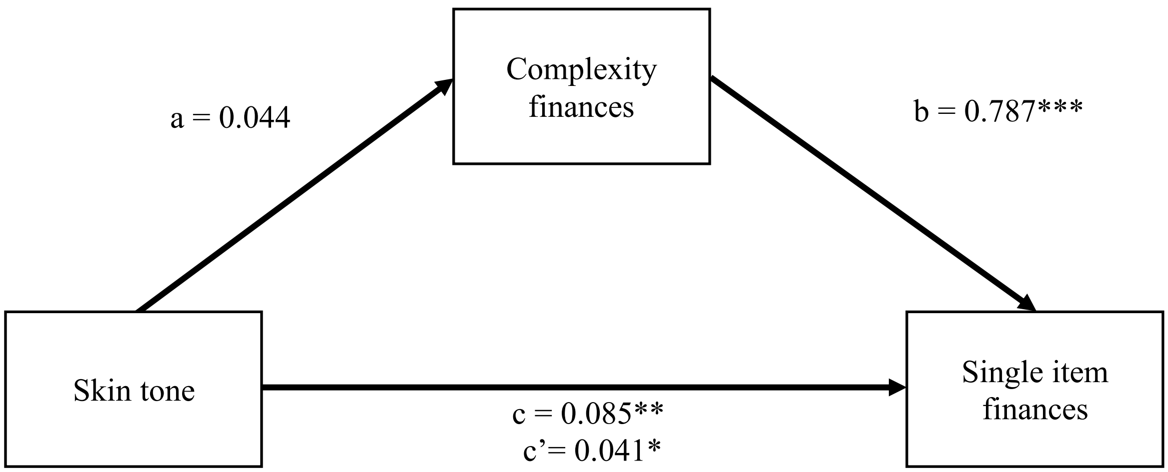
H3 Complexity Mediation Analysis Summary for Finances, DV Single Item Finances, No Covariates

Relationship	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Skin tone -> Complexity finances -> Single item finances	0.085 (0.004)	0.051 (0.042)	0.0343	0.0019	0.067	Mediation

Note. All results are unstandardized effect sizes

Figure 28

Complexity Finances: H3 Mediation Analysis Summary for Finances, DV Single Item Finances, No Covariates



**p < .05, ** p < .01, *** p < .001*

Table 47

Complexity Finances: H3 Mediation Analysis Summary for Finances, DV Single Item Finances, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.091 (0.002)	0.055 (0.026)	0.0356	0.0048	0.0667	Mediation
Technology use	0.046 (0.116)	0.028 (0.267)	0.0181	-0.0129	0.0485	Non-significant
Technology use and income	0.0527 (0.070)	0.0326 0.191	0.0201	-0.0105	0.0504	Non-significant

Note. All results are unstandardized effect sizes

Table 48

Complexity Social Media: H3 Mediation Analysis Summary for Social Media, DV Global Facial Recognition Technology Use, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.083 (0.000)	0.042 (0.009)	0.0403	0.0191	0.0623	Mediation
Technology use	0.043 (0.016)	0.022 (0.157)	0.021	0.003	0.0391	Mediation
Technology use and income	0.048 (0.007)	0.027 (0.090)	0.0214	0.0034	0.04	Mediation

Note. All results are unstandardized effect sizes

Table 49

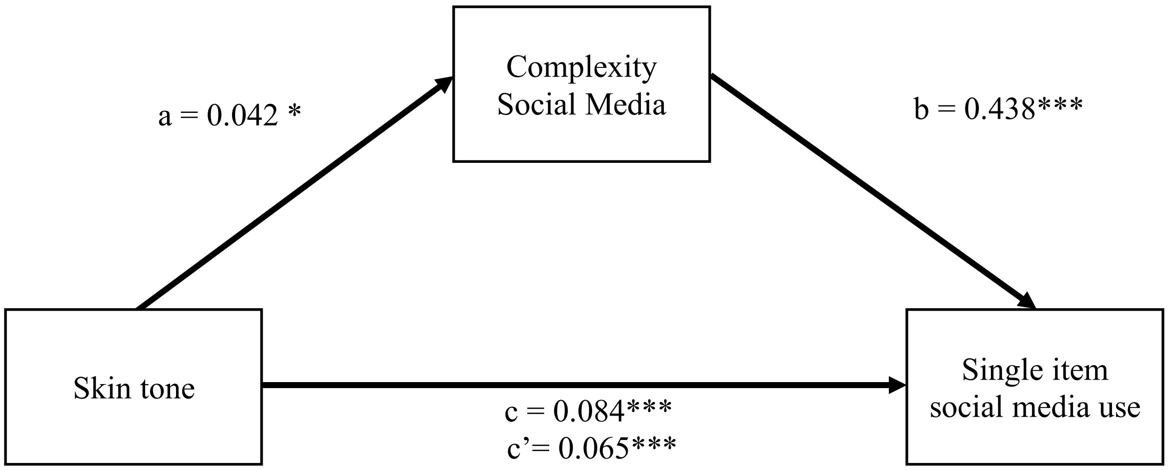
H3 Complexity Mediation Analysis Summary for Social Media, DV Single Item Social Media Use, No Covariates

Relationship	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Skin tone -> Complexity social media -> Single item social media use	0.084 (0.000)	0.065 (0.004)	0.018	0.0013	0.0355	Mediation

Note. All results are unstandardized effect sizes

Figure 29

Complexity Social Media: H3 Mediation Analysis Summary for Social Media, DV Single Item Social Media Use, No Covariates



**p < .05, ** p < .01, *** p < .001*

Table 50

Complexity Social Media: H3 Mediation Analysis Summary for Social Media, DV Single Item Social Media Use, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.085 (0.000)	0.066 (0.003)	0.0186	0.0021	0.0355	Mediation
Technology use	0.055 (0.018)	0.043 (0.053)	0.0118	-0.003	0.0266	Non-significant
Technology use and income	0.055 (0.018)	0.043 0.051)	0.0116	-0.0037	0.0265	Non-significant

Note. All results are unstandardized effect sizes

Table 51

Complexity Image Sensors: H3 Mediation Analysis Summary Image Sensors, DV Global Image Sensor Use, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval	Conclusion

				Lower bound	Upper bound	
Income	0.030 (0.044)	0.026 (0.075)	0.0039	-0.0021	0.0102	Non-significant
Technology use	-0.009 (0.516)	-0.010 (0.478)	0.0007	-0.0029	0.0043	Non-significant
Technology use and income	-0.006 (0.668)	-0.007 (0.627)	0.0007	-0.0033	0.0043	Non-significant

Note. All results are unstandardized effect sizes

Table 52

H4 Observability Mediation Analysis Summary for Phone Unlock, DV Global Facial Recognition Technology Use, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.083 (0.000)	0.063 (0.000)	0.020	0.007	0.0341	Mediation
Technology use	0.045 (0.013)	0.034 (0.053)	0.011	0.0008	0.0221	Mediation
Technology use and income	0.049 (0.007)	0.050 (0.004)	-0.0009	-0.0138	0.0113	Non-significant

Note. All results are unstandardized effect sizes

Table 53

H4 Observability Mediation Analysis Summary for Phone Unlock, DV Single Item Phone Unlock, No Covariates

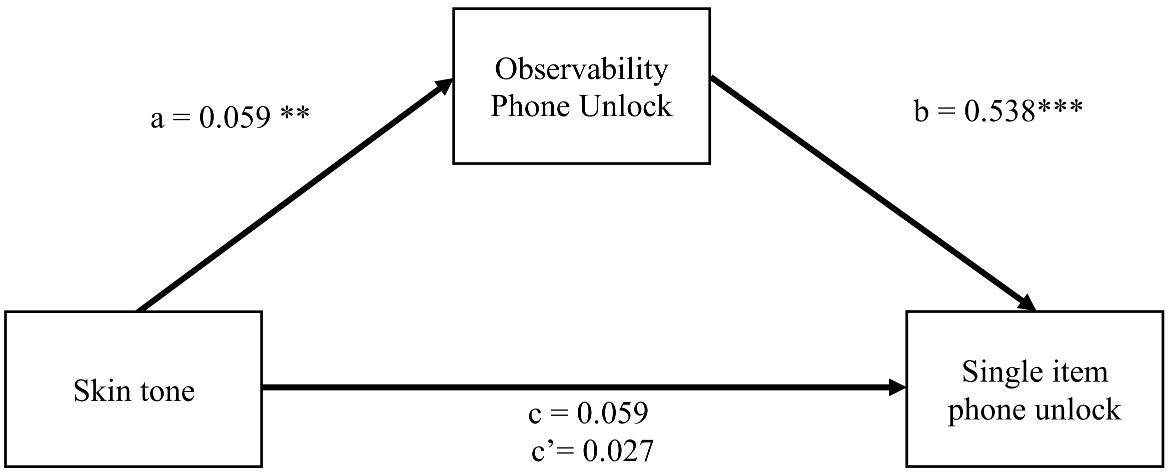
Relationship	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Skin tone -> Observability phone unlock -> Single	0.059 (0.061)	0.027 (0.364)	0.032	0.0089	0.055	Mediation?

item facial recognition technology use

Note. All results are unstandardized effect sizes

Figure 30

Observability Phone Unlock: H4 Mediation Analysis Summary for Phone Unlock, DV Single Item Facial Recognition Technology Use, No Covariates



**p < .05, ** p < .01, *** p < .001*

Table 54

H4 Observability Mediation Analysis Summary for Phone Unlock, DV Single Item Phone Unlock, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.064 (0.038)	0.033 (0.256)	0.0311	0.0094	0.0527	Mediation?
Technology use	0.019 (0.523)	0.001 (0.977)	0.0185	0.0008	0.0379	Mediation?
Technology use and income	0.0258 (0.394)	0.007 (0.811)	0.0189	0.0011	0.0381	Mediation?

Note. All results are unstandardized effect sizes

Table 55

H4 Observability Mediation Analysis Summary for Finances, DV Global Facial Recognition Technology Use, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.082 (0.000)	0.053 (0.003)	0.0292	0.013	0.0469	Mediation
Technology use	0.044 (0.015)	0.0264 (0.116)	0.0176	0.0038	0.0321	Mediation
Technology use and income	0.0482 (0.007)	0.0298 (0.077)	0.0184	0.0045	0.0331	Mediation

Note. All results are unstandardized effect sizes

Table 56

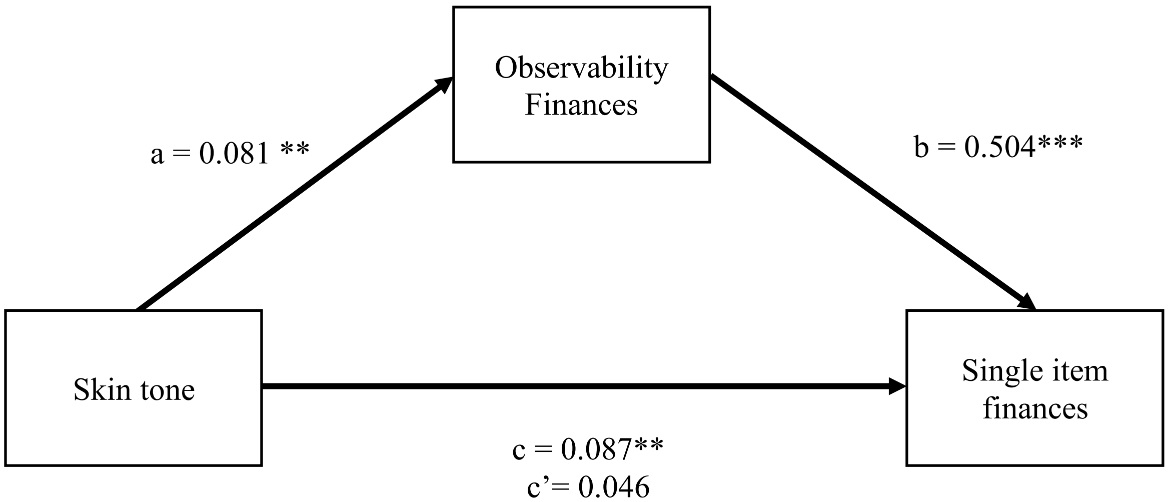
H4 Observability Mediation Analysis Summary for Finances, DV Single Item Finances, No Covariates

Relationship	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Skin tone -> Observability finances -> Single item finances	0.087 (0.004)	0.046 (0.099)	0.0409	0.0185	0.0659	Mediation

Note. All results are unstandardized effect sizes

Figure 31

Observability Finances: H4 Mediation Analysis Summary for Finances, DV Global Facial Recognition Technology Use, No Covariates



**p < .05, ** p < .01, *** p < .001*

Table 57

H4 Observability Mediation Analysis Summary for Finances, Single Item Finances, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.093 (0.002)	0.053 (0.059)	0.0404	0.0181	0.0639	Mediation
Technology use	0.047 (0.106)	0.0220 (0.428)	0.0252	0.0062	0.0456	Mediation?
Technology use and income	0.0540 (0.064)	0.0275 (0.322)	0.0264	0.0078	0.0469	Mediation?

Note. All results are unstandardized effect sizes

Table 52

H4 Observability Mediation Analysis Summary for Social Media, Global Facial Recognition Technology Use, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.026 (0.077)	0.026 (0.076)	0.0003	-0.0059	0.0059	Non-significant
Technology use	-0.012 (0.380)	-0.011 (0.409)	-0.0008	-0.0066	0.0035	Non-significant
Technology use and income	-0.009 (0.508)	-0.008 (0.542)	-0.0008	-0.0061	0.0036	Non-significant

Note. All results are unstandardized effect sizes

Table 58

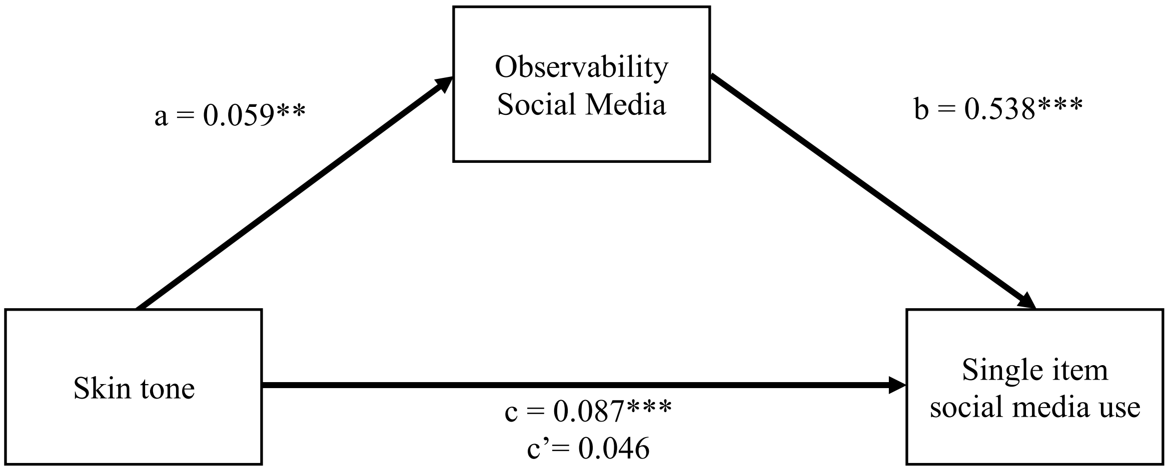
H4 Observability Mediation Analysis Summary for Social Media, DV Single Item Social Media Use, No Covariates

Relationship	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Skin tone -> Observability social media -> Single item social media	0.087 (0.004)	0.046 (0.099)	0.0409	0.0185	0.0659	Mediation

Note. All results are unstandardized effect sizes

Figure 32

Observability Social Media: H4 Mediation Analysis Summary for Social Media, DV single item social media use, No Covariates



*p < .05, ** p < .01, *** p < .001

Table 59

H4 Observability Mediation Analysis Summary for Social Media, Single Item Social Media Use, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.085 (0.000)	0.066 (0.003)	0.0186	0.0021	0.0355	Non-significant
Technology use	0.055 (0.018)	0.043 (0.053)	0.0118	-0.003	0.0266	Non-significant
Technology use and income	0.0550 (0.018)	0.0434 (0.053)	0.0116	-0.0037	0.0265	Non-significant

Note. All results are unstandardized effect sizes

Table 60

H4 Observability Mediation Analysis Summary for Image Sensors, Global Image Sensor Use, Covariates Summary

Covariate included	Total effect	Direct Effect	Indirect Effect	Confidence interval		Conclusion
				Lower bound	Upper bound	
Income	0.0260 (0.077)	0.0257 (0.076)	0.0003	-0.0059	0.0059	Non-significant
Technology use	-0.012 (0.380)	-0.011 (0.409)	-0.0008	-0.0066	0.0035	Non-significant
Technology use and income	-0.009 (0.508)	-0.008 (0.542)	-0.0008	-0.0061	0.0036	Non-significant

Note. All results are unstandardized effect sizes

Table 61

RQ1 Linear Regression. IV Perception of Skin Tone Bias in Algorithms, DV Trialability Phone Unlock

Covariates	Adjusted R^2	β	*SE*	*t*	*p*	95% CI
None	-0.001	-0.012	0.030	-0.389	0.697	[-0.072, 0.048]
Income	0.004	-0.014	0.030	-0.470	0.638	[-0.074, 0.0456]
Technology Use	0.054	-0.014	0.030	-0.408	0.684	[-0.072, 0.0472]
Income and Technology Use	0.054	-0.015	0.030	-0.481	0.630	[-0.074, 0.045]

Table 62

RQ1 Linear Regression. IV Perception of Skin Tone Bias in Algorithms, DV Trialability Finances

Covariates	Adjusted R^2	β	*SE*	*t*	*p*	95% CI
None	0.007	-0.093	0.034	-2.72	0.007	[-0.161, -0.026]
Income	0.017	-0.094	0.034	-2.736	0.006	[-0.162, -0.027]
Technology Use	0.060	-0.096	0.034	-2.800	0.005	[-0.162, -0.029]
Income and Technology Use	0.061	-0.096	0.034	-2.806	0.005	[-0.163, -0.029]

Table 63

RQ1 Linear Regression. IV Perception of Skin Tone Bias in Algorithms, DV Trialability Social Media

Covariates	Adjusted R^2	β	*SE*	*t*	*p*	95% CI
None	-0.000	0.014	0.029	0.485	0.628	[-0.043, 0.071]
Income	0.000	0.014	0.029	0.47	0.636	[-0.043, 0.071]
Technology Use	0.023	0.009	0.029	0.317	0.751	[-0.048, 0.067]
Income and Technology Use	0.022	0.009	0.029	0.313	0.754	[-0.048, 0.066]

Table 64

RQ1 Linear Regression. IV Perception of Skin Tone Bias in Algorithms, DV Trialability Image Sensors

Covariates	Adjusted R^2	β	*SE*	*t*	*p*	95% CI
None	-0.001	-0.011	0.025	-0.435	0.663	[-0.061, 0.039]
Income	-0.002	-0.013	0.026	-0.493	0.622	[-0.062, 0.038]
Technology Use	0.02	-0.011	0.026	-0.426	0.670	[-0.061, 0.039]
Income and Technology Use	0.022	-0.012	0.026	-0.475	0.635	[-0.048, 0.066]

A third, exploratory research question was preregistered with the OSF. The results of that research question are reported here.

RQ3. Are there differences among the diffusion of innovation items between the different contexts?

Table 65

Means, Standard Deviations for Compatibility Ratings Between the Four Technology Contexts

Context	Mean	SD
Phone Unlock	3.39	1.43
Finances	3.08	1.44
Social Media	2.68	1.36
Image Sensors	3.84	1.06

There was a significant effect of context on compatibility score on compatibility ratings at the $p < 0.001$ level (F(3,3366) = 114.7, $p < 0.000$, η2 = 0.093). There were significant differences between all pairs of variables.

Table 66

Means, Standard Deviations for Complexity Ratings Between the Four Technology Contexts

Context	Mean	SD
Phone Unlock	3.91	1.00
Finances	3.63	1.12
Social Media	3.75	1.00
Image Sensors	3.96	0.935

There was a significant effect of context on compatibility score on complexity ratings at the $p < 0.001$ level (F(3, 3377) = 18.73, $p < 0.000$, η2 = 0.016). There were significant differences between the finances and phone unlock, finances and image sensors, social media and image sensors and social media and phone unlock.

Table 67

Means, Standard Deviations for Trialability Ratings Between the Four Technology Contexts

Context	Mean	SD
Phone Unlock	3.79	1.13
Finances	3.27	1.28
Social Media	3.72	1.07
Image Sensors	3.87	0.948

There was a significant effect of context on trialability score on compatibility ratings at the $p < 0.001$ level ($F(3, 3382) = 49.08$, $p < 0.000$, $\eta 2 = 0.042$). There were significant differences between finances and all other contexts, and between social media and image sensors.

Table 68

Means, Standard Deviations for Observability Ratings Between the Four Technology Contexts

Context	Mean	SD
Phone Unlock	3.64	1.09
Finances	2.96	1.20
Social Media	3.73	1.04
Image Sensors	4.09	0.944

There was a significant effect of context on observability score on compatibility ratings at the $p < 0.001$ level ($F(3, 3385) = 166.1$, $p < 0.000$, $\eta 2 = 0.128$). There were significant differences between all pairs of variables except social media and phone unlock.

Table 69

Means, Standard Deviations for Relative Advantage Ratings Between the Four Technology Contexts

Context	Mean	SD
Phone Unlock	3.29	1.36
Finances	3.05	1.35
Social Media	2.72	1.23
Image Sensors	3.55	1.08

There was a significant effect of context on Relative Advantage score on compatibility ratings at the $p < 0.001$ level ($F(3, 3379) = 66.58$, $p < 0.000$, $\eta 2 = 0.055$). There were significant differences between all pairs of variables.

Table 70

Means, Standard Deviations for Reinvention Ratings Between the Four Technology Contexts

Context	**Mean**	**SD**
Phone Unlock	2.33	1.19
Finances	2.32	1.19
Social Media	2.43	1.20
Image Sensors	2.48	1.17

There was a significant effect of context on Relative Advantage score on compatibility ratings at the $p < 0.05$ level (F(3, 3379) = 3.423, $p = 0.016$, $\eta 2 = 0.003$). There were significant differences between image sensors and finances ($p = 0.035$).