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Research Paper

Agricultural workers as key practitioners for agricultural technology adoption in California's Central Valley

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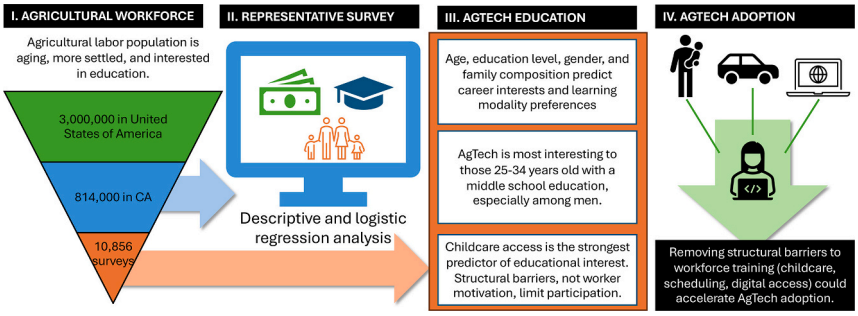
HIGHLIGHTS

- Farmworker community survey (n = 10,856) identifies structural barriers to agricultural technology workforce development.
- Structural costs, not worker motivation, limit human capital investment.
- Interest in agriculture technology (16.5%) exceeds general agriculture (5.3%).
- Middle school-educated men age 25–34 are most interested in agriculture technology.
- Childcare access is the strongest predictor of educational interest (OR = 5.97).

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: The digital transformation of agriculture (Agriculture 4.0) promises to address labor shortages, climate variability, and rising labor costs. However, adoption remains fragmented, due in part to a disconnect between technological development and the latent capacity of the incumbent workforce. The prevailing narrative of agricultural technology adoption often frames farm labor as a static constraint to be replaced, overlooking the potential for workforce augmentation and the value of farmworker expertise. Drawing on human capital theory and digital divide scholarship, this study examines whether the binding constraints on agricultural technology workforce development is worker interest or structural access to training.
METHODS: A public dataset of 10,856 survey responses from farmworker communities in California's Central Valley was collected through a community-engaged research framework via trusted community messengers. Geospatial analysis validated landscape-level representation, and logistic regression (binomial and multinomial) identified predictors of career interest, learning modality preference, and structural barriers to training.
RESULTS and CONCLUSIONS: Contrary to prevailing narratives, results revealed significant latent capacity in the workforce: 1786 respondents (16.5%) were interested in training pathways for agricultural technology, concentrated among men ages 25–34 with middle-school education. However, structural barriers impede workforce development. Childcare access was the single strongest predictor of interest in returning to school

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(odds ratio 5.97), functioning as critical infrastructure rather than as a social benefit. Internet access was not predictive of which training modality respondents preferred once they responded, but strongly predicted whether they engaged with the modality question at all, suggesting the digital divide shapes participation more than preference. We concluded that a primary limitation to agricultural technology adoption is not a lack of worker interest, but the shortage of accessible training infrastructure.

SIGNIFICANCE: This study provides empirical evidence that farmworker communities can drive agricultural technology adoption when structural barriers to training are addressed. By grounding the analysis in human capital theory and digital divide scholarship, the findings demonstrate that childcare, digital access, and flexible scheduling function as the structural costs of human capital investment for this population. The results offer a roadmap for inclusive digitalization that treats workforce development infrastructure as integral to agricultural systems design.

1. Introduction

Agricultural production in high-value cropping systems, such as California's Central Valley, faces a destabilizing convergence of pressures. Labor costs are rising with labor shortages, pushing production costs higher (Charlton, 2024; Hill and Martin, 2025). Simultaneously, climate change is driving environmental pressures including drought, heat, and wildfire smoke, threatening crop yields and making traditional manual labor increasingly hazardous (Kabeshita et al., 2023). Automation offers a solution with serious implications for current agricultural workforce, including training to adopt new techniques and tools (Hill et al., 2025).

Agriculture 4.0 integrates cyber-physical systems, autonomous machinery, artificial intelligence, and data-driven precision management in farm production operations (Maffezzoli et al., 2022). As a paradigmatic shift, building on Industry 4.0 principles, Agriculture 4.0 promises to address labor shortages, climate variability, and rising input costs of fertilizer, applications and fuel through increased automation and optimization (Miranda et al., 2019; Vărzaru, 2025). However, this technological framing captures only part of what the transition represents. Agriculture 4.0 is increasingly understood as a socio-technical transformation involving organizational, behavioral, and cultural change across the agri-food system (Barman et al., 2026; Klerkx and Rose, 2020; Rose et al., 2021). Divergent visions of what digital agriculture should become further complicate any assumption that participation follows automatically from technological capability (Lioutas et al., 2026). Narratives centered on productivity gains and environmental benefits have left the social dimension of this transition, including who is equipped to participate in it and on what terms, comparatively undertheorized (Rose et al., 2021).

While robotic and digital tools are available, on-farm adoption in specialty crops remains low relative to the potential benefits for profitability and sustainability (Gil et al., 2023; Prasad et al., 2023). The adoption gap is further driven by disconnection between the technological solutions and end users (Rotz et al., 2019). A scoping review of 200 social and behavioral science studies on digital agriculture found that dominant narratives framing digitalization as a solution to agricultural challenges have outpaced critical engagement with the distributional consequences of these transitions (McGrath et al., 2023). Many of the innovators developing new technology for agriculture, do not have practical experience working in food systems and therefore might overlook key design requirements (Fielke et al., 2020). Farmers in turn, often cannot afford the technology, feel it is not a good fit for their farm, find resulting data challenging to interpret, and are frustrated by the inability to repair or modify the equipment (Carolan, 2020; Kernecker et al., 2020).

Another challenge of technology adoption relates to the role of the agricultural workforce in the adoption process. Workers operate the equipment and experience its impact on labor conditions but rarely participate in purchase or implementation decisions. Research indicates that worker involvement in technology evaluation correlates positively with adoption rates, suggesting that further technology adoption research needs to incorporate workers into the analysis rather than focusing exclusively on farm owners or managers (Cofre-Bravo et al., 2019). Case study research on inclusive innovation in agricultural contexts has demonstrated that meaningful inclusivity requires moving beyond designing technologies "for" end users to designing "with" them, a distinction with particular implications for hired agricultural labor (Ndege et al., 2024). Hierarchical structures, language barriers, and lack of formal feedback mechanisms prevent workers from communicating the benefits or limitations of technologies to decision-makers, dampening diffusion (Catalini and Tucker, 2017).

Many farming systems rely on farmworkers whose jobs are often seasonal, short-term, or contracted through labor contractors. Farmworkers develop deep familiarity with cropping systems but may need training in specialized skills required to operate advanced technology (Mock et al., 2024). While growers make adoption decisions, farmworkers are the end users of advanced technologies such as harvest assisting robots or pack-in-field practices. The existing career structure has intense physical demands and offers limited upward mobility with few formalized pathways from field labor to supervisory, technical, or management roles (Castillo et al., 2025; Ramos, 2018). Industry retains the historical perception that the farmworker population is more mobile than settled. Increasing participation in the H2-A visa program, a federal temporary visa system for seasonal agricultural labor, may reinforce this perception (Luckstead and Devadoss, 2019). However, research demonstrates that farmworker populations are increasingly rooted in specific locations and specializing in cropping systems (Chandrasekaran, 2021; Hill et al., 2025; Martin, 1998). This misunderstanding encourages the view that farmworkers are substitutable labor, discouraging investment in training for a workforce whose technical and agricultural knowledge is, in practice, difficult to replace (Carlisle et al., 2019; Klocker et al., 2020). Creating a pathway for the farmworker workforce to engage with emerging agricultural technology would improve the design and adoption processes. In California and other high-labor-cost regions, high wages and labor shortages are jointly accelerating investment mechanization (Hamilton et al., 2022; Martin, 2024).

The current agricultural system has few mechanisms to transition experienced agricultural workers into skilled agricultural technology operators who maintain, troubleshoot, use, and optimize digital agricultural technology (Erickson et al., 2018). Without investing in professional pathways for this workforce, the industry risks losing agronomic, mechanical, crop-specific, climatic, and institutional knowledge, further delaying the promised efficiency gains of digital agriculture (Eastwood et al., 2017; Rotz et al., 2019). Precedents from manufacturing, mining, and healthcare demonstrate that experienced workers bring irreplaceable situational awareness to digitized workplaces, handling non-routine events that automated systems cannot (Hersh et al., 2010; Hirsch-Kreinsen, 2016; Rogers et al., 2019). These examples highlight the value of experienced workers for their situational awareness in the digitized workspace and ability to handle non-routine events that machines cannot troubleshoot.

Despite the critical role of the workforce in the Agriculture 4.0 socio-technical transition, existing research largely treats farm labor as a static input. However, researchers have identified that the labor force that grows the food is rapidly changing in California, Texas, and Florida

(Fung et al., 2023). Another gap in the research is the lack of study on career aspirations and ambitions of farmworkers, as more work has been focused on the educational outcomes of children of farmworkers than the workers themselves (Bejarano and Valverde, 2012; Delgado and Becker Herbst, 2018; Martinez and Cranston-Gingras, 2006). Little empirical data exists on the current workforce's willingness to adopt new technologies, their career aspirations within the emerging sector, and the barriers to their professional development.

This study draws on two complementary theoretical traditions. Human capital theory frames education and training as investments in which individuals weigh expected returns against costs and constraints (Becker, 1993; Inwood, 2017). Within this framework, demographic characteristics represent existing human capital stock, family structure creates both motivation for investment and competing demands on resources, and access to resources constitute the structural costs of human capital acquisition. However, classical human capital theory has been critiqued for treating educational investment as an individual rational choice while obscuring the structural inequalities of race, class, and gender that shape labor market returns (Beach, 2009). This limitation is particularly acute for agricultural workers, whose skills and knowledge acquired through field experience are systematically undervalued in formal credentialing systems (Hagan et al., 2014). Second, digital divide scholarship provides a framework for understanding unequal access to the benefits of technological transitions (Van Dijk, 2005, 2020). This scholarship distinguishes a resource-access divide, unequal physical access to the infrastructure needed to use digital technology, from a usage divide, unequal ability to participate in and benefit from digital processes once resource access is available (Van Dijk, 2005). In agricultural contexts, these divides intersects with existing inequities of race, farm size, and rural geography (Rotz et al., 2019). Together these frameworks motivate our focus on both who expresses interest in agricultural technology careers and what structural conditions enable or prevent access to training.

This exploratory study provides the first large-scale empirical characterization of farmworker community educational aspirations and capacity for agricultural technology adoption. The objectives are to characterize workforce capacity for Agriculture 4.0 adoption and identify structural barriers to training access. We address three guiding research questions: how interested the agricultural workforce is in technical career pathways, particularly jobs in agricultural technology operation, maintenance, and innovation; what demographic and structural factors predict interest and willingness to pursue training; and what logistical conditions are required for accessible workforce development programs. Our analysis of 10,856 survey responses uses descriptive analysis to characterize the demographic distribution of interest in agricultural technology careers, and logistic regression analysis to identify structural predictors of training participation. The study was conducted in California's Central Valley, an area characterized by high labor inputs in high heat and low-water conditions for diverse cropping systems including high-value orchards and vineyards as well as row crops with divergent agricultural technology availability for each system. While the Central Valley region represents an intensive and exceptional production system rather than a generalizable model, the workforce dynamics examine here characterize farmworker communities across labor-intensive agricultural regions, providing evidence-based insights for inclusive digitalization strategies.

2. Methods

2.1. Background: Central Valley case study

California's Central Valley is a globally significant food production region facing acute pressures driving technology adoption. The region's high-value specialty crop production relies heavily on approximately 814,000 predominantly Spanish-speaking hired workers during peak season (Ornelas et al., 2022; U.S. Department of Agriculture, National Agricultural Statistics Service, 2022). Convergent pressures from labor shortages, rising labor costs, and intensifying climate impacts, including drought, extreme heat, and wildfire smoke, threaten both crop yields and worker safety (Charlton, 2024; Hill et al., 2025; Hill and Martin, 2025; Kabeshita et al., 2023). Rising labor costs reflect both California's minimum wage increasing from $10.50 per hour in 2017 to $16.90 per hour in 2026 (California Department of Industrial Relations, 2024) and a growing reliance on the H-2A guest worker visa program which requires employers to provide housing and transportation, pay wages that are federally mandated to be higher than the state minimum, and navigate significant administrative processes (Luckstead and Devadoss, 2019; Martin, 2024). These conditions create strong economic incentives for growers to adopt automated and digital agricultural technologies while also raising critical questions about workforce capacity to adapt to farm transitions driven by exogenous factors (Gil et al., 2023; Rotz et al., 2019; Visser et al., 2024).

This study is focused on the San Joaquin Valley, the southern portion of California's Central Valley. Hot, dry summers and warm, wet winters define the Mediterranean climate. Agriculture composes 15% of GDP for key production region counties including Tulare and San Joaquin (Hanak et al., 2019). Irrigated row crops, fruit and nut orchards, table and wine grape vineyards, and dairy farms dominate the landscape of 5 M acres (Espinoza and Viers, 2024). The agricultural industry in the state generates $60 billion annually in gross cash receipts, with some of the nation's top grossing counties located in the study area (California Department of Food and Agriculture, 2026). However, there are several countervailing factors affecting the long-term sustainability of agricultural production in the region including climate change, water regulations, and labor shortages (Bernacchi et al., 2020; Hanak et al., 2019).

This study examines the conditions under which agricultural community members express interest in career pathways and educational re-engagement. Based on human capital theory, demographic characteristics are treated as existing human capital stock and access to childcare, transportation, and internet as structural costs of education investment (Becker, 1993; Lai and Widmar, 2021; Lee et al., 2026; Liebman et al., 2017). However, existing research has not examined how these factors operate specifically in agricultural contexts or for populations considering jobs in agricultural technology operation and maintenance. The regression models include a three-way interaction term between age, gender, and education level to capture how workforce capacity is distributed across subgroups. The analysis also examines logistical preferences for training delivery to identify priorities for accessible program design. Variables reflect the survey instrument developed for agricultural workforce development program planning (ARKEN Strategies, 2026). While data collection employed community engaged methods (Kindon et al., 2007), this secondary analysis works with the existing survey structure to characterize previously unmeasured constructs within agricultural communities rather than testing predetermined hypotheses.

2.2. Study context and programmatic goals

We analyzed a public dataset originally collected to inform the design of a competency-based agricultural technology certificate program at community colleges in the Central Valley, California, USA (ARKEN Strategies, 2026). The data collection followed a community-engaged research framework that prioritized the centrality of the worker in the design of educational interventions (Harrison et al., 2021; Kindon et al., 2007; Luger et al., 2020). Unlike curricula developed solely by academic or industry experts, this approach posits that effective workforce development requires understanding the lived constraints, aspirations, and existing technical expertise of the incumbent workforce. The survey instrument was designed to identify the specific logistical and pedagogical conditions required to facilitate enrollment among a population that faces systemic barriers to participation in

higher education.

2.3. Data collection and sampling strategy

Surveys were administered by community organization employees and volunteers in Spanish and English during the agricultural production season (March–August 2023). Data collection sites included community events, work sites, and outreach programs. Being involved in agriculture was not a requirement of participation. Participation was voluntary. Declining to take the survey did not affect access to the community event; participants could discontinue participation at any time.

Though this paper is focused on farmworkers, the interpretation of the study is limited because the survey did not include a factor that clearly describes the respondents current or prior experience with agriculture. Given the locations and events where surveys were conducted and the profile of the community organizations who led data collection, the survey population likely consists of farmworkers and farmworker family, friends, and community members. Based on the geography, language, rate of pay, and survey methodology, the results are representative of the educational interests of farmworkers and farmworker-adjacent communities. Farmworkers are classified separately from packing, processing, and transport workers under federal and state systems like the North American Industry Classification System and California's Taxonomy of Programs for instructional evaluation, though the work often shares similar repetitive tasks, strenuous conditions, and low pay. Many community members work multiple jobs across the food production and processing system in a given year (Ornelas et al., 2022). This diversified perspective may be represented in the sample.

As part of the US Economic Development Agency outreach program, data subsequently made public in the Zenodo repository and is available for secondary analysis (ARKEN Strategies, 2026). As a secondary analysis of the public dataset collected by a non-academic entity from which name and contact information was removed Institutional Review Board approval was not required. A non-probability sampling method precludes the calculation of a traditional response rate. There are 11,249 adult (over 18 years of age) respondents.

2.4. Survey instrument

The 34-question online web instrument assessed three primary dimensions: foundational demographics such as age and family structure, logistical constraints to education such as internet access and childcare needs, and aspirations regarding specific career pathways and preferred learning modalities. These dimensions aligned with the research objectives of characterizing workforce interest in technical careers, identifying predictors of interest, and determining the conditions required for accessible training.

2.5. Data validation

The public dataset ($N = 11{,}249$) excluded respondents who did not report their age to ensure all participants could be verified as adults over 18 years of age. The data were filtered to ensure robust statistical comparisons across demographic groups. First, the sample was restricted to respondents identifying as male or female. Respondents identifying as non-binary ($n = 37$) and those who did not report their gender ($n = 121$) were excluded because these subgroups were too small to produce stable estimates within a three-way interaction framework. This is a limitation of this study. Future research should prioritize targeted sampling to better understand the experiences of gender-diverse individuals. Finally, respondents with missing education levels ($n = 257$) were removed, resulting in a sample of 10,856 respondents.

2.6. Statistical analysis

Outcome variables were constructed through categorical aggregation. Career interest variables were constructed from a multi-select question that allowed respondents to indicate interests in multiple training pathways simultaneously and enter qualitative 'other' responses which were recoded using keyword matching to categorize respondents into one or more interest groups. Each career pathway was then coded as a binary outcome variable (interested vs. not interested) for the analysis of each interest group. Preferred learning modality was classified hierarchically: respondents who selected both remote and in-person options were categorized as preferring 'Hybrid,' while those who exclusively selected one mode were categorized as preferring either 'Remote' or 'In-Person' learning. Those who selected neither were categorized as 'No Preference.' Predictor variables like age and education level were grouped to ensure sufficient cell counts for interaction modeling. The 'Some College' education category includes vocational training, often offered at community colleges. Data cleaning, feature engineering, and statistical analysis were conducted in R version 4.5.1.

To identify the determinants of educational and career aspirations, we employed Generalized Linear Models. For binary outcomes such as interest in agricultural technology, we utilized Binomial Logistic Regression. For the preferred learning modality, which is a four-level categorical outcome, we utilized Multinomial Logistic Regression via the *nnet* package in R (Venables and Ripley, 2002). Base models included a three-way interaction term between age, gender, and education level to capture the intersectional dynamics of the workforce demographics. Control variables included marital status, number of dependents, and access to logistical resources including internet and transportation. Model significance was assessed using Type III Analysis of Deviance to account for the unequal group sizes across demographic categories in the observational data. Due to the granular nature of the three-way demographic interactions, certain subgroups exhibited low frequencies which led to quasi-complete separation in standard logistic regression. To address this, we employed Firth's Penalized Likelihood regression via the *logistf* package when separation was detected, to ensure stable parameter estimates and unbiased standard errors. Since logistic regression coefficients for variables involved in interactions are conditional on the levels of the other interacted variables, demographic interaction effects are presented as predicted probabilities, allowing direct comparison across profiles while holding control variables constant. Given that the two non-reference outcome levels of the modality model (In-Person, Remote) share a common baseline category (No Preference Selected), a direct pairwise comparison between them was conducted via Wald tests on the difference between their coefficients, using the fitted model's existing coefficient covariance matrix; no model refitting or re-leveling was required.

3. Results

3.1. Spatial and demographic characteristics of the workforce

Survey responses are spatially concentrated along the Highway 99 corridor (Fig. 1), aligning with regional population centers and agricultural production zones (Teitz et al., 2005; U.S. Census Bureau, 2025). When survey responses are expressed as a percentage of county-level agricultural workers (Fig. 1B), the sample is shown to capture a significant cross-section of the labor force, with response densities in key production counties like Fresno and Tulare ranging between 5% and 15% of the total hired agricultural workforce estimated by the USDA Census of Agriculture (U.S. Department of Agriculture, National Agricultural Statistics Service, 2022).

The demographic profile of the sample (Fig. 2) is representative of the regional agricultural workforce. The median age bracket was 35–44 years, with the modal group being 25–34 years. This aligns with the age distribution reported in the National Agricultural Workers Survey for

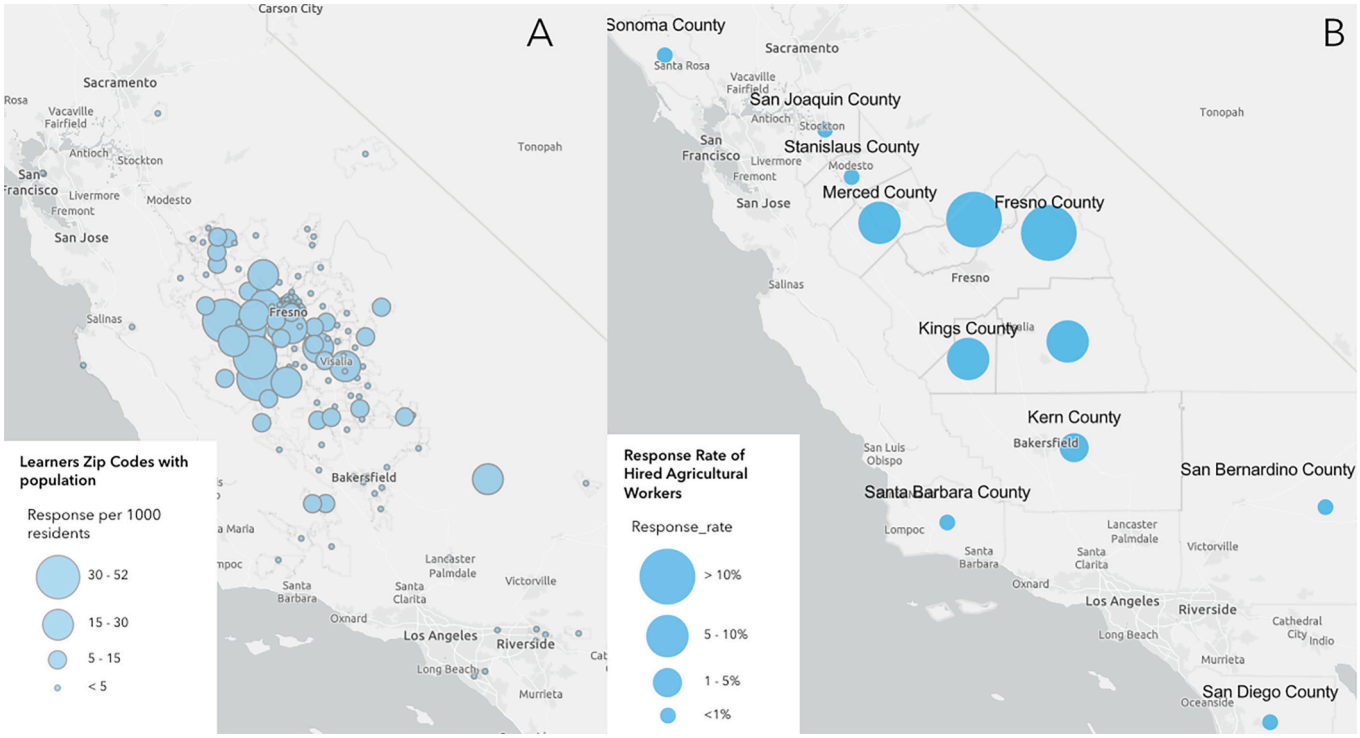

Fig. 1. Spatial distribution of survey respondents in California's Central Valley. (A) Response density per 1000 residents in Zip Code Tabulation Areas (2020 U.S. Census). (B) Responses as a percentage of hired agricultural workers by county (2022 USDA Census).

California (Ornelas et al., 2022). Women were represented at a rate of 44%, which is slightly higher than typical field labor estimates but consistent with the broader agricultural community including packing and processing sectors (Lopez, 2024; Ornelas et al., 2022). The sample skews female due to women being more likely to access school resources for children (such as at the backpack giveaways). The workforce is heavily integrated into family structures with 62% reporting being married or in a domestic partnership and 77% reporting dependents.

3.2. Educational baseline and systemic constraints

Formal educational attainment is low, with 69% of respondents reporting an education level of middle school or less (Fig. 3A). The remaining 31% have completed at least high school or the equivalent General Education Development certification (GED), including 7.5% who have engaged in higher education. Respondents show a high valuation of education; 79% of respondents agree that "education is important" or "education is very important" (Fig. 3B).

The gap between educational valuation and attainment is driven in part by identifiable systemic constraints. Analysis of qualitative responses to the question of why respondents ended their education (Appendix A) indicates financial barriers and the imperative to work were reported 7065 times, outnumbering other factors. Geographic barriers such as remote home location, lack of transportation, and migration were also constraints. Notably, lack of interest was reported rarely (306 mentions), reinforcing that the educational deficit is a function of access and economic pressure rather than worker apathy.

3.3. Workforce educational aspirations

When presented with potential educational programs, the respondents demonstrated significant interest in general education and technical upskilling (Table 1). English as a Second Language (ESL) as the most selected option overall (60%). Among the technical upskilling options those within the category of skilled trades were collectively the most selected, including welding, solar panel installation, mechanics, carpentry, plumbing, construction, and heating, ventilation, and air conditioning. Though interest in general agriculture was selected by only 571 respondents (5.3%), interest in agricultural technology (AgTech) was selected by 1786 respondents (16.5%), representing a distinct sub-population of the workforce interested in digital transformation.

This AgTech-interested demographic differs from the general sample (Table 1). They are predominantly male (80%) and concentrated in the 25–34 age bracket. Fig. 4 illustrates that this interest is highest among those with a middle school education, suggesting that AgTech is viewed as a viable upward mobility pathway for workers who have not yet attained a high school equivalency. This contrasts with interest in healthcare, which skews female, and skilled trades, which skews towards older age groups with less formal education.

3.4. Predictors of interest in agricultural technology

A binomial logistic regression model identified significant predictors of AgTech interest (Appendix B). The regression modeling results describe which demographic and resource factors predict interest in agricultural technology careers. The analysis revealed a statistically significant three-way interaction between age, gender, and education level ($p = 0.02$), indicating that the appeal of AgTech is not uniform across the workforce (Fig. 5). The model indicates that interest is particularly resilient among mid-career men with middle school education.

Family structure acts as a motivator rather than a deterrent for this specific career track. Having dependents significantly increased the odds of AgTech interest (Appendix B). Respondents with three or more dependents had 2.11 times higher odds of being interested in AgTech compared to those with no children, suggesting that workers may view technology roles to secure better economic outcomes for their families. These factors inform educational structures and were therefore selected to better support respondent engagement with education.

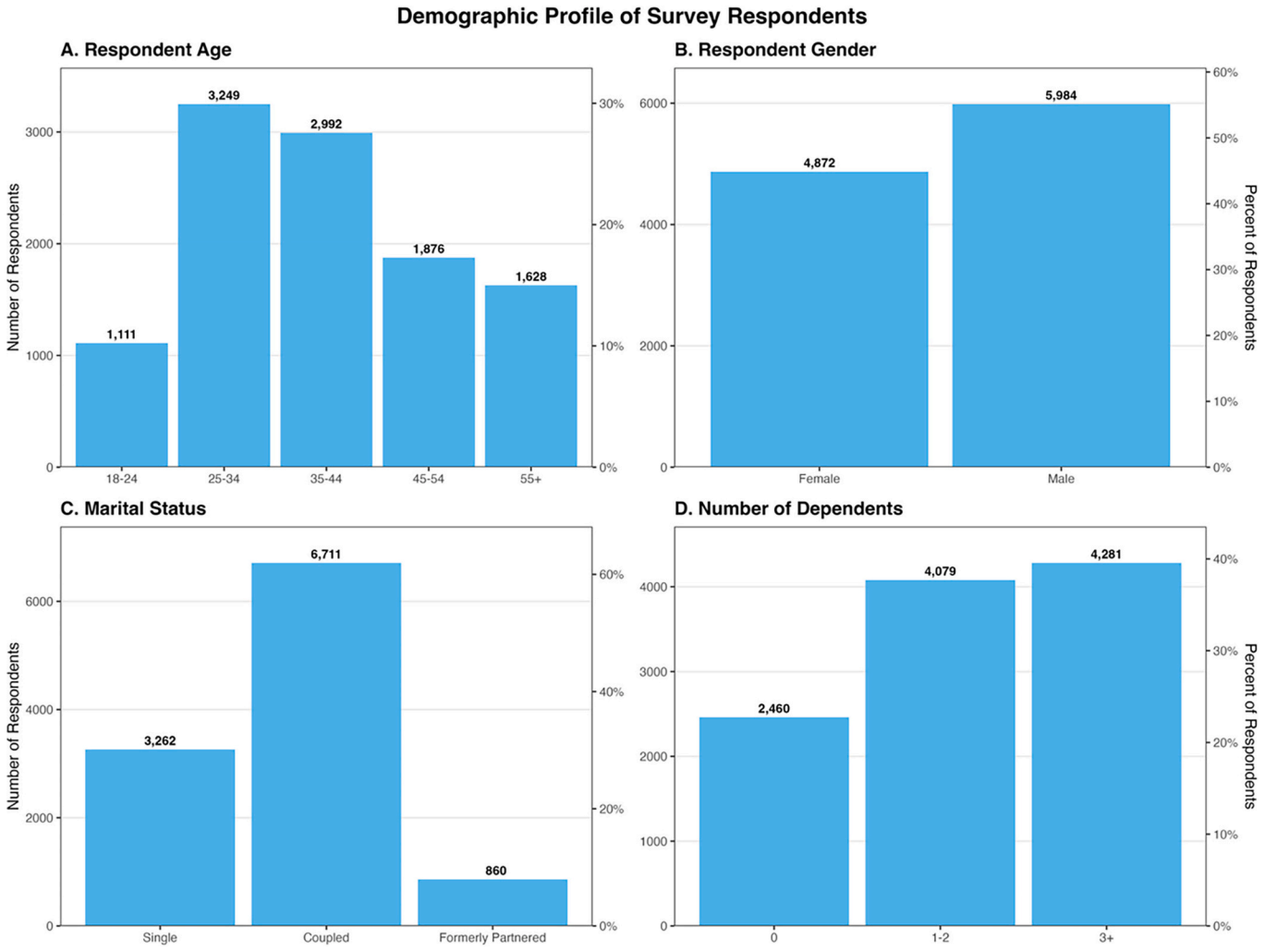

Fig. 2. Demographic profile of survey respondents ($N = 10{,}856$). (A) Age distribution. (B) Gender distribution. (C) Marital status. (D) Number of dependents.

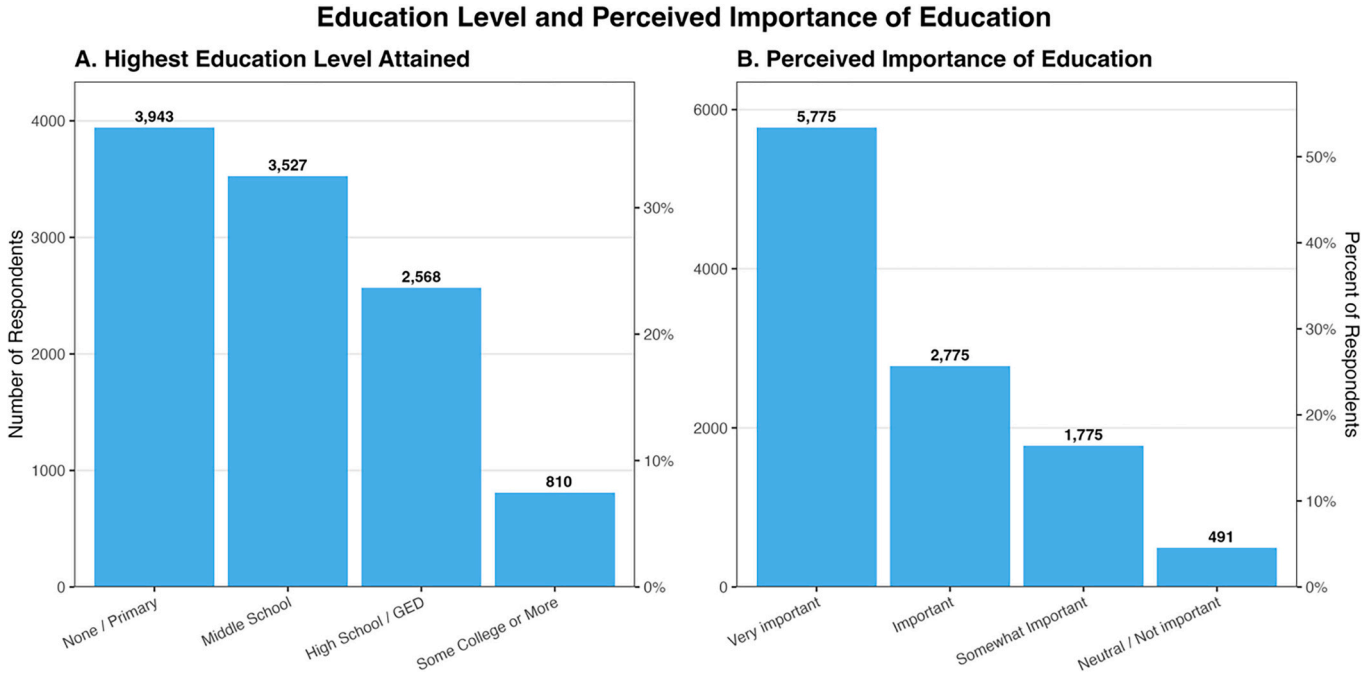

Fig. 3. Educational baseline of the agricultural workforce. (A) Highest level of formal education attained. (B) Respondent Perceived importance of education.

Table 1
Demographic profile of respondents by stated career interest. Modal categories represent the most frequent response within each interest group.

Demographic Profile of Respondents by Stated Career Interest				
Summary statistics for each group of interested respondents				
Interest	Total Interested	% Male	Modal Age Group[1]	Modal Education[1]
ESL	6553	55%	25–34	Middle School
General Education Diploma	3221	58%	25–34	Middle School
Skilled Trades (e.g. welding, solar panel installation)	2589	82%	35–44	None or Primary
Healthcare	2142	28%	25–34	High School or Equivalent
AgTech	1786	80%	25–34	Middle School
General Agriculture	571	80%	25–34	Middle School

[1] Modal category represents the most frequent response within each group.

3.5. Predictors of re-engagement with education

The analysis of structural predictors reveals which barriers prevent or enable engagement in training programs. General interest in returning to school is high (60%), but conversion of interest to enrollment remains low (4%). The logistic regression model for educational re-engagement highlights childcare as the critical lever for conversion (Appendix C). As shown in Fig. 6A, the need for childcare support was the most powerful predictor in the model. The odds of being interested in returning to school were 5.97 times higher for respondents who indicated a need for childcare compared to those who did not. Access to internet (Fig. 6B) and transportation (Fig. 6C) also showed positive, statistically significant associations with educational interest, confirming that logistical friction points act as primary determinants of workforce adaptability. Pay rate (Fig. 6D) was not a significant predictor, likely because most respondents earning above minimum wage reported only marginally higher pay. In the overall sample, 8534 respondents (78%) reported feeling financially insecure. Notably, all predicted probabilities dip slightly at the high school/GED level before increasing again for respondents with some college experience, suggesting that high school completion itself may represent a perceived terminal credential, whereas those with prior college experience have already demonstrated a propensity to re-engage with formal education. Another possibility is that high school graduates and GED holders may occupy a gap in the educational system in which they are overqualified for basic adult education programs but lack the confidence or prerequisites for college-level technical programs.

3.6. Optimization of knowledge transfer modalities

To facilitate workforce transition, educational delivery must align with the logistics of prospective learners. The analysis of preferred modalities and scheduling reveals the conditions required for accessible training. Survey results indicate a clear preference for flexibility, with 44% of respondents selecting remote learning as a preferred modality, probably due to its implication of asynchronous learning. This is consistent with respondents' preferred time for classes. Most respondents indicated a preference for courses offered during non-working hours, specifically evenings (n = 4032; 40%) and weekends (n = 1872; 18.5%), rather than during weekday mornings (n = 1220; 12%) or afternoons (n = 1175; 11.6%). Additionally, 1820 respondents

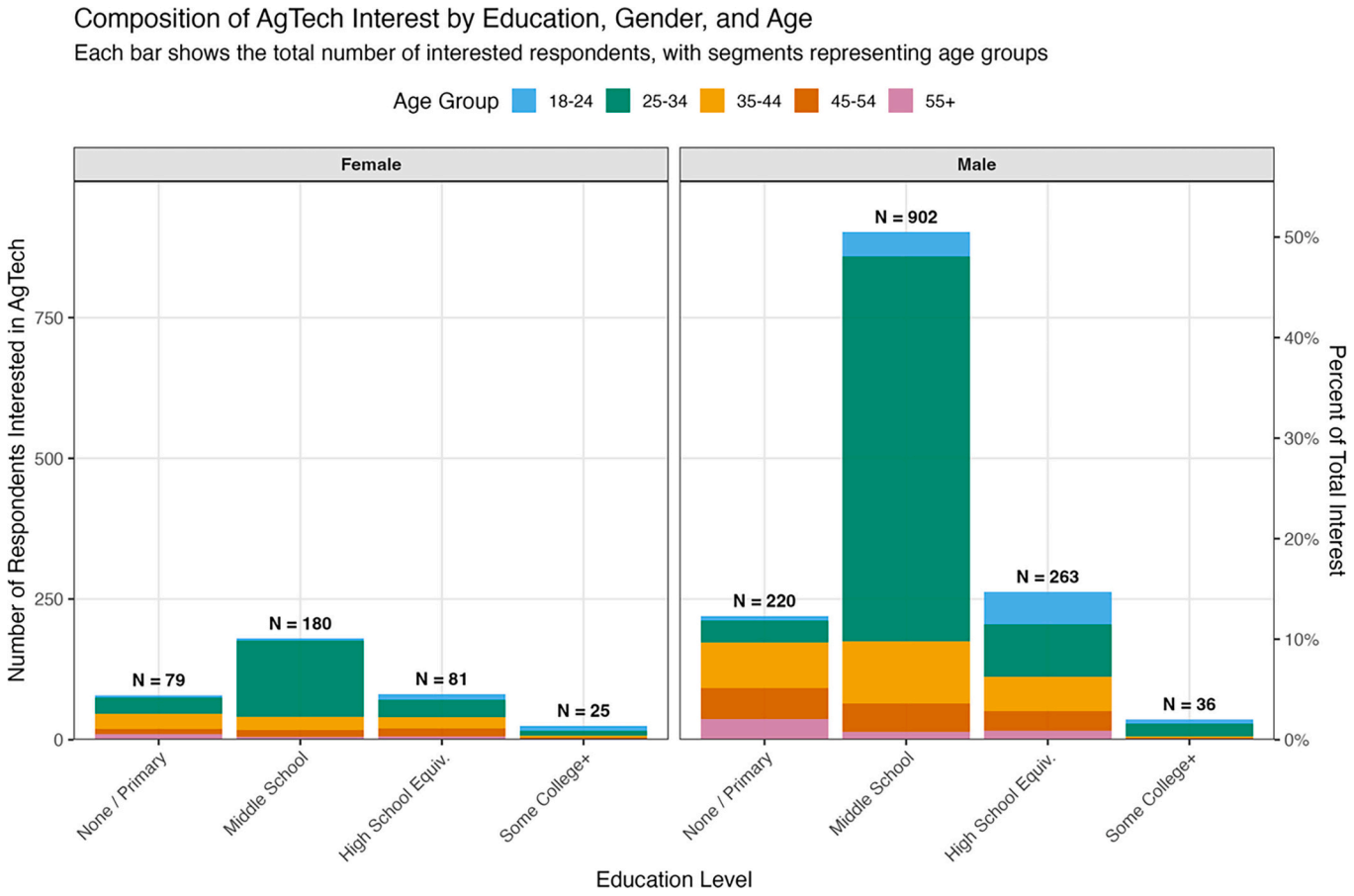

Fig. 4. Composition of AgTech interest by education, gender, and age. Stacked bars represent the count of respondents interested in agricultural technology careers, segmented by age group.

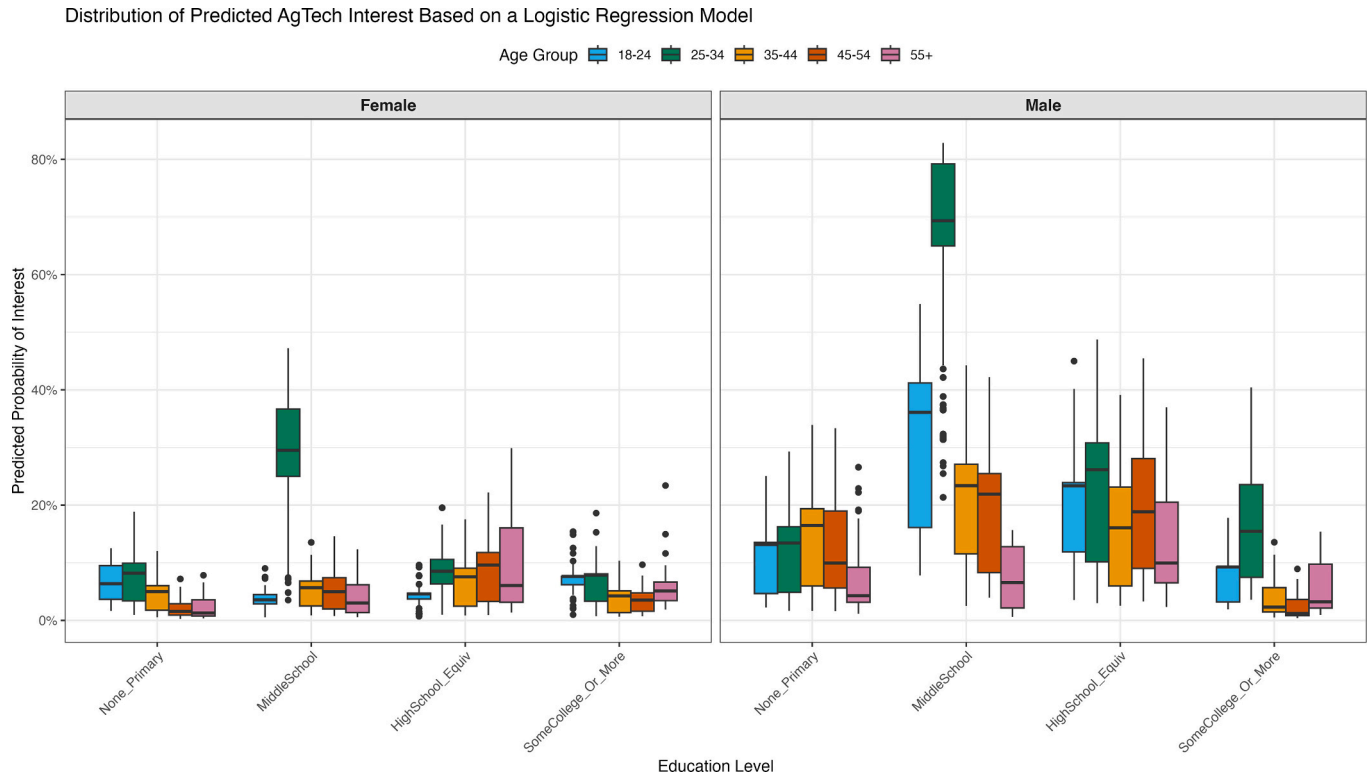

Fig. 5. Predicted probability of interest in Agricultural Technology. Boxplots represent the distribution of predicted probabilities derived from a binomial logistic regression model including a three-way interaction between age, gender, and education level.

(18%) reported not having time for classes.

The multinomial logistic regression analysis (Appendix D) reveals that modality preference varies significantly by career-pathway interest, relative to respondents who did not select any modality preference. Respondents interested in Skilled Trades and AgTech were each associated with significantly higher odds of preferring in-person and remote learning over no preference (odds ratio 9.32 and 4.63 for in person, and 7.70 and 10.10 for remote, respectively). Since respondents who selected both in-person and remote options were categorized as preferring 'hybrid' (Section 2.6), the in-person and remote categories analyzed here reflect exclusive preference for a single delivery mode. A direct contrast test isolating this comparison (Appendix E) shows that Skilled Trades interest was associated with significantly higher odds of preferring in-person over remote delivery (odds ratio 1.21, 95% CI [1.07, 1.37], $p < 0.01$), while AgTech interest was associated with significantly lower odds of preferring in-person over remote delivery (odds ratio 0.46, 95% CI [0.39, 0.54], $p < 0.01$; Appendix E).

Internet access was significantly associated with selecting a modality preference of any kind, rather than leaving the question unanswered (odds of 4.65, 4.67, and 8.32 for in-person, remote, and hybrid delivery, respectively, relative to no preference selected; Appendix D). However, the direct contrast test found no significant association between internet access and the choice between in-person and remote delivery specifically once preference was expressed (odds ratio 0.99, 95% CI [0.89, 1.11], $p = 0.91$; Appendix E).

4. Discussion

4.1. The latent capacity for socio-technical transition

Agriculture 4.0 requires coupling advanced techniques with capable human operators. human capital theory frames education as an investment in which individuals weigh expected returns against costs and constraints (Becker, 1993). Read through that lens, the majority of respondents expressing interest in returning to school (60%) indicates that expected returns to investment in education are perceived as high in this population. A consistent pattern emerges in digital agriculture adoption research, where individual-level interest frequently outpaces institutional capacity to provide accessible training (Fragomeli et al., 2024; Rotz et al., 2019). A parallel case comes from precision agriculture adoption in China, where policy support and extension access, not technology perception alone, drove adoption among farm managers (Han et al., 2026). The findings of this study extend that pattern by quantifying the gap at scale within communities of the hired agricultural workforce, a population that is rarely centered in this literature. The shortage of AgTech labor documented elsewhere therefore reflects a failure to build accessible pathways for investment in education against a backdrop of structural inequality (Baur and Iles, 2023; Wong and Moghimi, 2025).

Agriculture functions in hyper-local and idiosyncratic environments where biological systems vary by field and season. Workers with agricultural experience possess experiential knowledge regarding crop physiology, specialized equipment operation, and harvest logistics that external technology companies, innovators, and new hires lack (Carlisle et al., 2019). Yet this knowledge is systematically undervalued in traditional and formal credentialing systems, a pattern well documented among immigrant worker populations (Hagan et al., 2014). By supporting upskilling for this demographic, the sector can retain this knowledge while layering on the necessary digital competencies. This strategy of labor augmentation rather than labor replacement aligns with the resilience goals of sustainable agricultural systems and rural economies (Hill et al., 2025).

AgTech, which lacks a definition in the survey and a practicing definition in the agricultural sector, appears to represent a place of possibility. Current agricultural workers likely have exposure to these technologies. For those working outside agriculture, AgTech may serve as an attractive entry point with greater perceived economic opportunity than traditional agricultural jobs. Interest in AgTech is concentrated

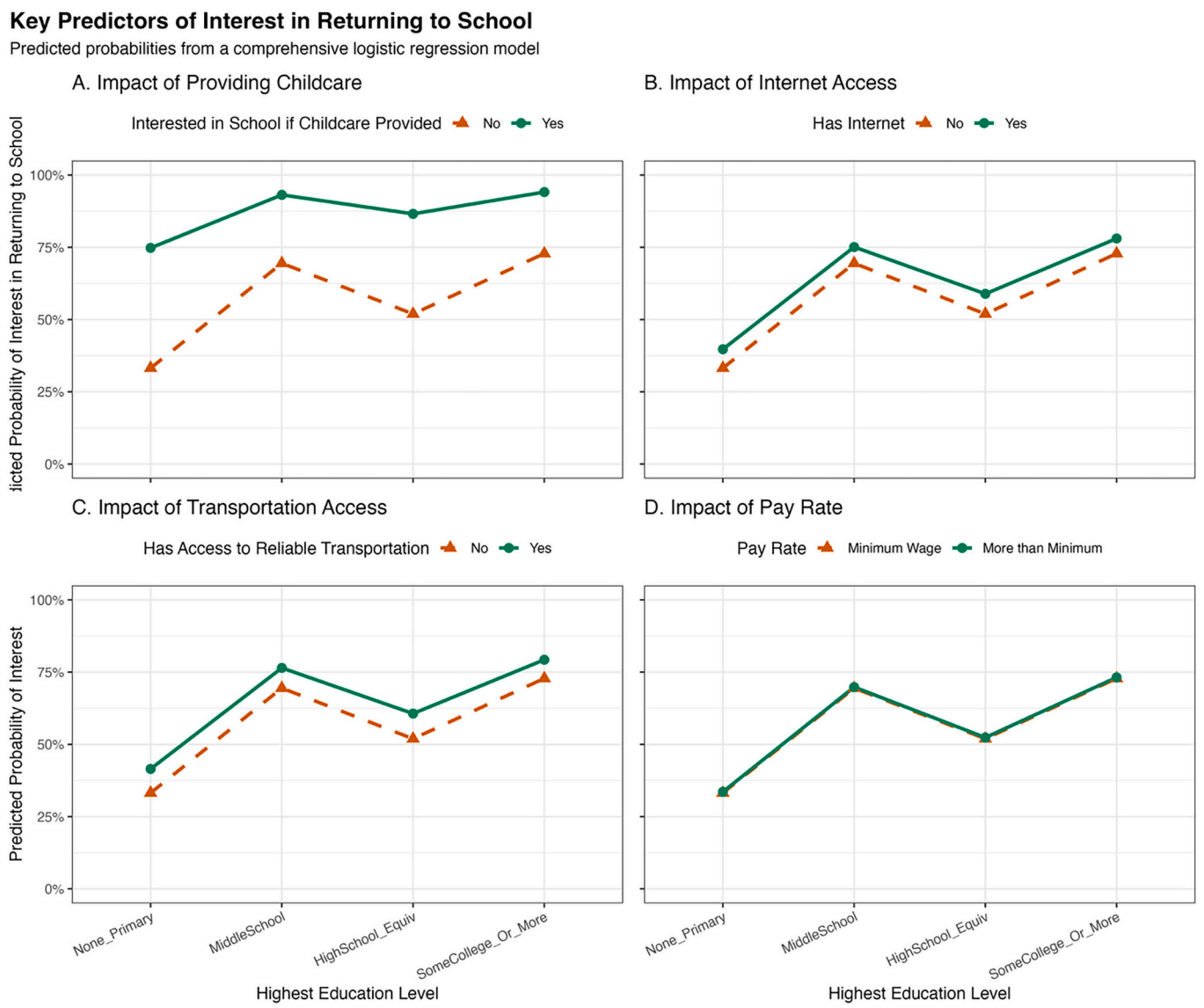

Fig. 6. Key predictors of interest in returning to school. Plots display predicted probabilities from a logistic regression model holding other variables constant. (A) Impact of childcare availability. (B) Impact of internet access. (C) Impact of reliable transportation. (D) Impact of pay rate (Minimum wage vs. Above minimum).

in mid-career men aged 25–34 with middle-school levels of education. Experience of the physical, mental, and economic hardships of agricultural labor while balancing dual pressures of supporting children and elders may be motivating their pursuit of a different career trajectory. This is consistent with the human capital theory's framing of investment as attractive when the gap between current and prospective earnings is largest (Becker, 1993). Expressed interest should be distinguished from workforce readiness. While these results demonstrate substantial demand for training pathways, the data capture aspirations rather than confirmed capacity. Translating this interest into effective workforce transition would require structured credentialing programs, employer engagement, and ongoing assessment of labor market demand for candidates with these qualifications (Fragomeli et al., 2024).

4.2. Systemic barriers and critical infrastructure

Even where latent human capital exists, converting interest into enrollment is constrained by systemic barriers. Treating this gap as a matter of individual motivation, without addressing what stands in the way, risks reproducing structural inequity classical human capital theory has been critiqued for obscuring (Beach, 2009).The data identify two concrete, addressable barriers: the availability of childcare, and unequal access to the internet connectivity needed to engage with training opportunities in the first place.

The strongest predictor of interest in returning to school was an affirmative response to a separate conditional question asking whether childcare availability would change that interest. Respondents who indicated this need had 5.97 times higher odds of interest in returnting to school (Appendix C). Respondents with caregiving responsibilities possess high motivation to upskill, likely driven by the economic imperative to support their dependents, yet face the steepest logistical barriers to participation. This finding extends research documenting that farmworker parents identify childcare access as a primary constraint on employment and training participation (Liebman et al., 2017). It also confirms that agricultural employers recognize childcare as a workforce investment that improves stability and retention (Lee et al., 2017). This pattern is consistent with the broader evidence that rural communities have significantly fewer licensed childcare slots per child than metropolitan areas, creating a structural deficit that constrains rural workforce development across sectors (Henning-Smith and Kozhimannil, 2016).

In a systems context, childcare cannot be viewed merely as a social

benefit. It functions as critical infrastructure, comparable to roads or broadband in structuring who can participate in the labor force (Li and Laughlin, 2024). The gendered division of caregiving labor in agricultural communities means that women disproportionately bear the costs of maintaining households and caring for dependents alongside paid work (Doss and Gottlieb, 2025; Fitting, 2025). A systematic global review of gender dynamics in climate-smart agriculture adoption extends this pattern beyond the California context, confirming that education and financial constraints are reported barriers for overall technology adoption, while extension services and social networks serve as critical enablers specifically for women (Gupta et al., 2026). These results suggest that offering childcare alongside education could function as a mechanism to bridge the gap between worker motivation and availability for training, reframing childcare from a private burden into a shared infrastructure that enables human capital investment.

The agricultural workforce also requires time flexibility to ensure availability for training. Given that financial necessity was the primary barrier to education cited by respondents (65%), this population cannot forgo income to attend training, and courses must therefore be offered outside of traditional business hours. Educational programs should also accommodate varying levels of literacy, languages, and learning preferences through asynchronous and competency-based delivery (Liebman et al., 2017). Without these support structures, a highly motivated workforce will remain locked in low-wage jobs due to resource constraints.

4.3. Aligning pedagogical modalities with workforce reality

The divergence in preferred learning modalities highlights the need for a diversified educational infrastructure. Understanding these preferences addresses the question of what logistical conditions are required for effective workforce development in agricultural communities. Of the career pathways studied, respondents interested in Skilled Trades were the only group in the dataset that significantly preferred in-person delivery, plausibly reflecting the pedagogical demands of physical skill acquisition that cannot be replicated remotely. The respondents interested in AgTech showed the opposite pattern expressing significantly more interest in both in-person and remote formats relative to the general population, but the direct contrast test shows a clear preference for remote over in-person learning within this subgroup (odds ratio 0.46 favoring remote, $p < 0.01$). This suggests AgTech-interested respondents are comfortable with, and may prefer, digitally delivered training, a notable finding given that AgTech is itself a digital technology domain.

Internet access showed no significant relationship with the choice between in-person and remote delivery once a respondent expressed a preference (Appendix E). Its association was instead with whether respondents engaged with the modality question at all, an effect of similar magnitude across in-person, remote, and hybrid options (Appendix D). Differential engagement with the modality question is itself evidence of digital exclusion as respondents without internet access are less likely to engage with the process of expressing a training preference at all. This finding extends research on Canadian farmers which found that connectivity determines technology adoption (McCaig et al., 2026) and a multi-country analysis identifying rural connectivity as a key driver of Agriculture 4.0 adoption (Da Silveira et al., 2026). It is consistent with the distinction between resource-access and usage divides in digital divide theory (Van Dijk, 2005).

Regardless of modality, most respondents indicate a preference for courses offered during non-working hours, specifically evenings and weekends, rather than during standard business hours. This confirms research on adult education participation that found rigid work schedules, and the financial barriers they secondarily reflect, are a primary barrier to enrollment (Radovan, 2024), reinforcing the necessity of offering training outside traditional business hours for populations with limited control over their work time.

4.4. Agriculture 4.0 as socio-technical transformation

Agriculture 4.0 is not simply an individual-skills or technology-adoption story, but a socio-technical transformation whose benefits are not evenly shared unless social sustainability is deliberately built into the transition rather than assumed as its byproduct (Rose et al., 2021; Steinke et al., 2024). Framing the fourth agricultural revolution primarily around productivity and environmental gains, while treating its social dimension as secondary, has left the workforce question undertheorized relative to its practical importance; multi-actor co-innovation frameworks that place farmers, workers, and other stakeholders inside the innovation process itself, rather than as its downstream recipients, offer one corrective (Barman et al., 2026; Rose et al., 2021). Comparative analysis across multiple countries confirms that adoption barriers rarely reduce to individual technology choices, instead reflecting interactions among farmers, policymakers, and technology vendors operating within distinct institutional and infrastructural environments (Barman et al., 2026). Divergent stakeholder visions of what digital agriculture should become, and for whom, further complicate any assumption that workforce inclusion follows automatically from technological capability (Lioutas et al., 2026). Digitalization and agroecological transition are themselves only partially aligned. Digital tools can support more complex, diversified farming systems, but can also reinforce the standardization and capital concentration that agroecological approaches resist (Bellon-Maurel et al., 2022). A full analysis at the level of socio-technical regime change is beyond what this dataset can support, but the workforce dimension examined here is itself one component of the broader institutional and infrastructural environment that determines whether agricultural innovation systems function inclusively or reproduce existing exclusions (Eastwood et al., 2017; Elsner et al., 2023).

Even if the specific barriers of cost and access identified here were resolved, equitable outcomes would not be guaranteed. Digital agriculture research documents how technological transition can intensify labor precarity through workforce bifurcation into technical and manual roles (Rotz et al., 2019), and participatory research in Germany finds that displacement risk concentrates among seasonal workers in labor-intensive horticultural systems structurally similar to this study's population (MacPherson et al., 2025). Digitalization can also increase worker surveillance and concentrate benefits among large-scale operations with capital to invest (Bampasidou et al., 2024). This is consistent with evidence that dominant narratives about agricultural digitalization have insufficiently addressed distributional consequences (McGrath et al., 2023). The digital divide in agricultural contexts intersects with existing inequities of race, gender, immigration status, and farm size to shape who captures the returns on technological change (Lee et al., 2026). The barriers documented here, caregiving and technology access, are not conditions to be cleared before workforce development begins; they are what it must address to succeed. Given the equity risks just described, expanding the supply of trained workers does not by itself determine who benefits from that investment. Building childcare access, flexible scheduling, and connectivity into training pathways from the outset, rather than treating them as implementation details, follows from that risk: without deliberate design, these same barriers are likely to determine who is excluded from an equitable Agriculture 4.0 transition, not merely who is inconvenienced by its adoption.

4.5. Limitations

The interpretation of these results is subject to specific limitations inherent to the study design. First, as a cross-sectional study, this analysis captures associations between demographic characteristics and expressed interests at a single point in time. Causal relationships between structural barriers and training participation cannot be inferred from these data.

Second, the survey utilized a convenience sample within community-

engaged research, rather than a random sample. While this approach enables access to a historically underrepresented population and yielded a geographically representative sample, results reflect community-level educational interests rather than individual-level values. Given the study's focus on economic development for a population affected by agricultural digitalization, the sampling method was appropriate for identifying accessible educational opportunities. Future studies should employ a more refined instrument that assesses prior agricultural experience and defines agricultural technology.

Third, the use of Spanish-language instruments likely excluded specific sub-populations of the workforce, most notably speakers of indigenous Mesoamerican languages and non-Hispanic immigrant groups. Future research should specifically serve these linguistic minority groups to ensure equitable access to workforce transition pathways for all who are currently involved in the work of growing food. Additionally, the survey's explicit focus on educational opportunities may have introduced social desirability bias. Respondents at community events might have been predisposed to express interest in training, potentially inflating the interest in returning to school beyond what might be observed in the broader workforce.

Fourth, the survey instrument did not explicitly define "Agricultural Technology" (*Tecnología en agricultura*) or "AgTech" (*AgTec*) for respondents. While this presents an interpretive challenge, it also highlights a strength of the findings. Even without a clear definition, this pathway was much more popular than "General Ag" (*Agronomía*), indicating it is perceived as a distinct departure from more familiar careers. It is possible that interest would be even higher if the specific nature of the roles were described and respondents were presented with a clear programmatic pathway. This ambiguity has specific implications for interpretation. The 16.5% of respondents interested in agricultural technology may therefore reflect varied conceptions of work along the agricultural value chain rather than uniform interest in field-based roles. This study's application of digital divide theory is limited to the resource-access dimension measured directly in the survey instrument; the skills-based dimension of the divide, while conceptually relevant to Agriculture 4.0 adoption, falls outside what this dataset can assess.

Finally, the survey did not collect data on the specific agricultural experience level of respondents. While the recruitment sites indicate that respondents are part of the agricultural community, we cannot verify the extent of their agricultural work experience or confirm that respondents interested in agricultural technology possess existing agronomic expertise. More broadly, this study documents workforce interest and identifies structural barriers to training access but does not assess labor market demand for agricultural technology roles or the capacity of existing educational institutions to deliver the required training at scale. Findings demonstrate interest in agricultural technology pathways rather than confirmed workforce readiness and claims about leveraging existing agricultural knowledge or retaining sector expertise cannot be empirically supported by this dataset. Future studies should confirm that respondents have experience in agriculture and correlate experience level with interest in new technologies. Continued qualitative and survey research on AgTech workers and learners will be an important resource for workforce development and the adoption of AgTech.

5. Conclusion and future directions

This study addresses three research questions regarding workforce capacity for Agriculture 4.0 adoption in California's Central Valley. The study found that agricultural communities express substantial interest in technical career pathways, with interest in agricultural technology exceeding that of general agriculture. Interpreted through a Human Capital Theory framework, the demographic and structural factors predicting these interests reveal that the binding constraint is not willingness to invest in new skills but the structural cost of doing so, with childcare access emerging as the strongest predictor of interest in returning to school. Meeting this demand requires evening and weekend scheduling and childcare support. Since internet access predicted whether respondents engaged with the modality question at all rather than which format they preferred, connectivity functions as a gatekeeper to participation, not merely a constraint on format.

Together, these findings provide empirical evidence that the primary constraint on farmworker community participation in digital agriculture is not a deficit of interest or ability, but the absence of accessible professional training and support infrastructure. Workforce development programs targeting agricultural technology adoption must treat childcare, internet access, and flexible scheduling as foundational infrastructure rather than ancillary support. Investments in farmworker education should be understood not as charitable interventions but as strategic investments in retaining the agronomic expertise that agricultural technology systems require to function effectively. These findings directly informed the development of the Farms Food Future Ag Systems certificate program, delivered by seven regional community colleges in the Central Valley beginning in 2024, whose outcomes warrant future evaluation.

As digitalization of agricultural systems accelerates globally, these findings suggest three critical avenues for future research. First, empirical studies should verify the agricultural experience and technical knowledge of community members to determine whether training programs leverage existing expertise or primarily serve new entrants. Second, research should examine whether including experienced agricultural workers in technological design improves adoption rates and user satisfaction. Third, longitudinal studies should assess whether regions that invest in agricultural workforce training demonstrate higher farm-level technology adoption rates compared with regions relying primarily on substitutable labor. The digital revolution in agriculture will need to prioritize, train, and retain the agricultural and technical expertise held exclusively by farmworkers to access the touted benefits for economic and environmental sustainability that agricultural technology promises.

CRediT authorship contribution statement

Kimberly J. Gibson: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Leigh A. Bernacchi:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Karen Aceves:** Writing – original draft, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Shobha Khanna:** Formal analysis, Data curation. **Joshua H. Viers:** Writing – review & editing, Visualization, Supervision, Software, Resources, Project administration, Methodology, Funding acquisition.

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The authors declare that they have no known competing financial

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- Organización Las Panchas (https://organizacionlaspanchas.org/)
- Unidad Popular Benito Juarez (https://www.unidadpopular.org/)
- Binacional of Central California (https://binationalca.org/)

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2026.104899.

Data availability

The data is publicly available at https://zenodo.org/doi/10.5281/zenodo.18201604

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