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Examining Agricultural Engineering Students' Views on the Usability of Artificial Intelligence in Agricultural Practices

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Abstract

This study aimed to examine the views of agricultural engineering students regarding the usability of artificial intelligence (AI) in agricultural practices, and to investigate whether these views differed by gender and class year. A total of 223 students enrolled in the faculties of agriculture at two different universities in Turkey participated in the study. Data were collected through a demographic information form and the AI Usability in Agriculture Scale (AUAS), developed specifically for this research. The AUAS consists of 15 items distributed across two factors: Perceived AI Potential (PAP) and Perceived Barriers to AI Adoption (BAR). Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) results confirmed the two-factor structure with acceptable fit indices (CFI = .96, RMSEA = .053). Independent samples t-tests indicated that female students had significantly higher PAP scores than their male counterparts ($p = .002$), while no significant gender difference was found for the BAR subscale. A one-way ANOVA revealed that perceived AI potential increased significantly across class years ($p = .001$), whereas no significant class-year effect was found for perceived barriers. These findings suggest that higher-year students are more optimistic about AI integration in agriculture, and that gender may influence how students perceive AI potential. Implications for agricultural education and curriculum development are discussed.

Keywords: Artificial intelligence, agriculture, agricultural engineering education, AI usability, scale development

Introduction

The rapid advancement of artificial intelligence (AI) technologies in recent decades has transformed virtually every sector of society, and agriculture is no exception. Precision agriculture, smart farming, and AI-driven decision support systems have begun to reshape how crops are grown, monitored, and harvested (Liakos et al., 2018). From machine learning algorithms that predict crop yields based on satellite imagery to deep learning models that detect plant diseases from photographs, AI applications hold considerable promise for enhancing agricultural productivity and sustainability (Kamilaris & Prenafeta-Boldú, 2018). In a country like Turkey, where agriculture constitutes a significant portion of the national economy and rural livelihoods, the adoption of AI in farming carries particular strategic importance.

Despite the potential of AI technologies, their adoption in agricultural settings remains uneven, often due to knowledge gaps, economic constraints, and attitudinal barriers among stakeholders (Wolfert et al., 2017). Agricultural engineering students represent a particularly important population in this regard, as they are the future professionals who will be responsible for integrating emerging technologies into farming systems. Understanding how these students perceive AI—both in terms of its potential and the barriers to its adoption—is therefore crucial for shaping effective educational curricula and policy interventions (Eastwood et al., 2019).

Research on AI attitudes in agricultural contexts has been growing, but most studies have focused on farmers and agricultural professionals rather than on students in pre-service agricultural education programs (Klerkx et al., 2019). Furthermore, studies examining how



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demographic variables such as gender and academic year influence AI perceptions in agricultural education remain scarce, particularly in the Turkish context. Gender differences in technology attitudes have been widely documented in other fields such as engineering and computer science (Beyer, 2014; Margolis & Fisher, 2002), but whether similar patterns exist in agricultural technology acceptance requires further investigation. Similarly, the effect of academic experience on technology attitudes—students who have advanced further in their studies may have developed more nuanced views of both the capabilities and limitations of AI—has not been systematically explored in agricultural education research.

Given these gaps, the present study sought to examine agricultural engineering students' views regarding the usability of AI in agricultural practices, and to explore whether these views varied by gender and class year. To this end, a new measurement instrument, the AI Usability in Agriculture Scale (AUAS), was developed and validated. This paper reports the psychometric properties of the AUAS alongside the substantive findings of the survey.

Purpose of the Study

The primary purpose of this study is to examine the views of agricultural engineering students on the usability of artificial intelligence in agricultural practices. More specifically, the study aims to: (a) develop and validate a psychometrically sound scale to measure AI usability perceptions among agricultural engineering students; (b) describe students' general perceptions of AI potential and perceived barriers to AI adoption in agriculture; and (c) determine whether these perceptions differ significantly based on gender and class year.

Importance of the Study

This study contributes to the literature in several important ways. First, it addresses a notable gap in agricultural education research by providing empirical data on how future agricultural engineers perceive AI-driven solutions. Second, the development and validation of the AUAS provides a reliable and contextually appropriate measurement tool that can be used in future research across different agricultural education settings. Third, by examining demographic differences in AI perceptions, the study offers practical guidance for instructors and curriculum designers who aim to foster positive attitudes toward technology adoption among diverse student populations. Finally, the findings have broader implications for agricultural policy and innovation diffusion in Turkey and other developing agricultural economies (Rogers, 2003).

Research Questions

This study was guided by the following research questions:

1. What are the psychometric properties (factor structure, reliability, and validity) of the AI Usability in Agriculture Scale (AUAS)?
2. What are the agricultural engineering students' general perceptions regarding the potential and barriers of AI in agriculture?
3. Do students' AI usability perceptions differ significantly based on gender?
4. Do students' AI usability perceptions differ significantly based on class year?

Method

Research Design

This study employed a descriptive-correlational survey design (Creswell & Creswell, 2018). Survey research is well-suited for describing the characteristics of a large population and for exploring relationships among variables. The cross-sectional data were collected during the spring semester of the 2023–2024 academic year.

Participants

Participants were 223 undergraduate students enrolled in the departments of agricultural engineering at two public universities in Turkey. Convenience sampling was used to recruit participants from available course sections. Of the 240 questionnaires distributed, 223 were returned in usable form, yielding a response rate of 92.9%. Table 1 presents the demographic characteristics of the sample.

Table 1

Demographic Characteristics of the Sample (N = 223)

Variable	n	%
Gender		
Female	124	55.6
Male	99	44.4
Class Year		
1st Year	61	27.3
2nd Year	58	26.0
3rd Year	55	24.7
4th Year	49	22.0
University		
University A	115	51.6
University B	108	48.4
AI Familiarity		
None	38	17.0
Basic	94	42.2
Intermediate	65	29.1
Advanced	26	11.7

Note. PAP = Perceived AI Potential; BAR = Perceived Barriers to AI Adoption.

As shown in Table 1, the sample comprised 124 female (55.6%) and 99 male (44.4%) students. With respect to class year, the distribution was relatively balanced across all four years. The majority of participants (82.2%) reported having at least a basic level of familiarity with AI technologies.

Data Collection Instruments

Data were collected using two instruments: a demographic information form and the AI Usability in Agriculture Scale (AUAS) developed by the authors of this study.

Demographic Information Form. The demographic form gathered information on participants' gender, class year, university affiliation, and self-reported level of familiarity with AI

technologies.

AI Usability in Agriculture Scale (AUAS). The AUAS was developed to assess agricultural engineering students' perceptions of AI usability in agricultural contexts. Scale development followed established procedures (DeVellis, 2017; Worthington & Whittaker, 2006), including: (a) a thorough review of the relevant literature on AI adoption in agriculture and technology acceptance (Davis, 1989; Venkatesh et al., 2003); (b) generation of an initial item pool of 28 items by a panel of three agricultural engineering faculty members and two educational technology specialists; (c) expert review for content validity by five academic experts, resulting in the reduction of the item pool to 20 items; and (d) a pilot study with 30 students not included in the main sample, which informed further item reduction. Items were rated on a five-point Likert-type scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

Scale Validation Procedures

To examine the factor structure of the AUAS, exploratory factor analysis (EFA) was conducted on a randomly selected half of the sample ($n = 111$), followed by confirmatory factor analysis (CFA) on the remaining half ($n = 112$). This split-sample validation approach is recommended to avoid capitalizing on chance and to provide an independent test of the factor structure (Floyd & Widaman, 1995).

Exploratory Factor Analysis. EFA was conducted using principal axis factoring with Promax rotation, which allows factors to correlate and is appropriate for psychological and educational constructs (Fabrigar et al., 1999). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was .87, and Bartlett's test of sphericity was statistically significant ($\chi^2 = 1,142.4$, $p < .001$), indicating that the data were suitable for factor analysis. A two-factor solution was retained based on the scree plot, eigenvalue criterion (eigenvalues > 1.0), and parallel analysis (Horn, 1965). Five items were removed due to low factor loadings ($< .40$) or high cross-loadings, resulting in a final 15-item scale. Factor 1, labeled Perceived AI Potential (PAP), comprised 8 items; Factor 2, labeled Perceived Barriers to AI Adoption (BAR), comprised 7 items. The two factors explained a cumulative variance of 59.7%. Table 2 presents the factor loadings and communalities for all items.

Table 2

Factor Loadings and Communalities from Exploratory Factor Analysis of the AUAS ($n = 111$)

Item	Factor 1 (PAP)	Factor 2 (BAR)	Communality
Item 1: AI can increase crop yield prediction accuracy	.78	.12	.62
Item 2: AI-based systems can optimize irrigation management	.81	.09	.67
Item 3: AI can improve pest and disease detection	.76	.14	.60
Item 4: AI contributes to soil analysis efficiency	.74	.17	.58
Item 5: AI can enhance precision agriculture applications	.80	.11	.65

Item 6: AI tools are useful for climate-related decisions	.72	.20	.56
Item 7: AI integration could transform agricultural education	.69	.23	.53
Item 8: AI application in farming increases productivity	.77	.15	.62
Item 9: Lack of training is a barrier to AI adoption	.16	.79	.65
Item 10: High cost limits AI use in agriculture	.10	.83	.70
Item 11: Infrastructure deficiency restricts AI adoption	.19	.76	.62
Item 12: Farmers' resistance hampers AI implementation	.22	.74	.60
Item 13: Policy and legal constraints limit AI adoption	.18	.77	.63
Item 14: Data privacy concerns deter AI use in farming	.21	.72	.57
Item 15: Lack of digital literacy is a major challenge	.14	.80	.66
Eigenvalue	5.82	3.14	
Variance Explained (%)	38.8	20.9	
Cronbach's α	.89	.87	

Note. PAP = Perceived AI Potential; BAR = Perceived Barriers to AI Adoption. Factor loadings $\geq .40$ are considered meaningful. Items are presented in their final scale order.

Confirmatory Factor Analysis. CFA was performed using the AMOS 24.0 software package to evaluate the fit of the two-factor model to the independent validation subsample ($n = 112$). Maximum likelihood estimation was employed. Model fit was evaluated using multiple indices: the χ^2/df ratio, the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), the Root Mean Square Error of Approximation (RMSEA), and the Standardized Root Mean Square Residual (SRMR), as recommended by Hu and Bentler (1999). The results indicated acceptable to good model fit: $\chi^2(89) = 141.7$, $\chi^2/df = 1.59$, CFI = .96, TLI = .95, RMSEA = .053 (90% CI [.037, .069]), SRMR = .061. These indices collectively support the two-factor structure of the AUAS. Cronbach's alpha coefficients were .89 for the PAP subscale and .87 for the BAR subscale, both of which indicate high internal consistency (Nunnally & Bernstein, 1994). The inter-factor correlation was $r = .31$ ($p < .001$), suggesting that while the two constructs are related, they are sufficiently distinct to be treated as separate factors.

Data Analysis

Descriptive statistics (mean, standard deviation, minimum, and maximum) were computed for each subscale and the total scale. To examine whether AI usability perceptions differed by gender, an independent samples t-test was conducted for each subscale. To examine whether

perceptions differed by class year, one-way analysis of variance (ANOVA) was performed, followed by Tukey's post-hoc test where significant omnibus effects were found. Effect sizes were calculated using Cohen's *d* for t-tests and eta-squared (η^2) for ANOVA. All analyses were conducted using SPSS 27.0. The significance level was set at $\alpha = .05$.

Findings

Descriptive Statistics

Table 3 presents descriptive statistics for the AUAS subscales and the total scale for the full sample ($N = 223$).

Table 3

Descriptive Statistics for AUAS Subscales and Total Scale ($N = 223$)

Variable	n	M	SD	Min	Max
PAP – Perceived AI Potential	223	3.71	0.72	1.25	5.00
BAR – Perceived Barriers to AI	223	3.45	0.81	1.14	5.00
Total Scale	223	3.59	0.68	1.40	5.00

Note. PAP = Perceived AI Potential (8 items, scored 1–5); BAR = Perceived Barriers to AI Adoption (7 items, scored 1–5).

As shown in Table 3, the mean score for the PAP subscale was $M = 3.71$ ($SD = 0.72$), which falls in the 'Agree' range of the five-point scale, suggesting that agricultural engineering students generally hold favorable views regarding the potential of AI in agricultural applications. The mean BAR score was somewhat lower ($M = 3.45$, $SD = 0.81$), indicating that participants also perceive notable barriers to AI adoption, though somewhat less strongly than they perceive AI's potential. The total scale mean was $M = 3.59$ ($SD = 0.68$), suggesting an overall moderately positive orientation toward AI usability in agriculture.

Differences by Gender

Independent samples t-tests were conducted to determine whether AUAS scores differed by gender. The results are presented in Table 4.

Table 4

Differences in AUAS Subscale Scores by Gender

Subscale	Female M (SD)	Male M (SD)	t	df	p	Cohen's d
PAP	3.84 (0.69)	3.55 (0.74)	3.07	221	.002	0.41
BAR	3.41 (0.83)	3.50 (0.78)	-0.83	221	.406	0.11
Total Scale	3.64 (0.67)	3.52 (0.69)	1.29	221	.198	0.17

Note. PAP = Perceived AI Potential; BAR = Perceived Barriers to AI Adoption. Cohen's *d*: small

= .20, medium = .50, large = .80 (Cohen, 1988).

As illustrated in Table 4, a statistically significant difference was found between female and male students on the PAP subscale, $t(221) = 3.07$, $p = .002$, Cohen's $d = 0.41$, with female students ($M = 3.84$, $SD = 0.69$) reporting higher perceived AI potential than male students ($M = 3.55$, $SD = 0.74$). The effect size was small to medium. No statistically significant gender difference was found for the BAR subscale, $t(221) = -0.83$, $p = .406$, or for the total scale score, $t(221) = 1.29$, $p = .198$.

Differences by Class Year

One-way ANOVA was conducted to examine whether AI usability perceptions differed across the four class years. The results are presented in Table 5.

Table 5

Differences in AUAS Subscale Scores by Class Year

Subscale	1st M (SD)	2nd M (SD)	3rd M (SD)	4th M (SD)	F	p	η^2
PAP	3.48 (0.74)	3.62 (0.71)	3.82 (0.69)	3.98 (0.68)	5.41	.001*	.069
BAR	3.52 (0.79)	3.48 (0.82)	3.41 (0.84)	3.37 (0.80)	0.87	.458	.012
Total Scale	3.50 (0.67)	3.56 (0.69)	3.63 (0.66)	3.69 (0.69)	1.48	.220	.020

Note. PAP = Perceived AI Potential; BAR = Perceived Barriers to AI Adoption. η^2 : small = .01, medium = .06, large = .14 (Cohen, 1988). Post-hoc Tukey tests for PAP showed significant differences between 1st and 3rd year ($p = .018$) and 1st and 4th year ($p = .003$) students.

As shown in Table 5, a statistically significant main effect of class year was found for the PAP subscale, $F(3, 219) = 5.41$, $p = .001$, $\eta^2 = .069$ (medium effect size). Post-hoc Tukey analyses revealed that fourth-year students ($M = 3.98$, $SD = 0.68$) perceived significantly higher AI potential than first-year students ($M = 3.48$, $SD = 0.74$; $p = .003$), and that third-year students ($M = 3.82$, $SD = 0.69$) also scored significantly higher on PAP than first-year students ($p = .018$). No significant differences emerged between adjacent class years. No significant main effect of class year was found for the BAR subscale, $F(3, 219) = 0.87$, $p = .458$, $\eta^2 = .012$, or for the total scale score, $F(3, 219) = 1.48$, $p = .220$, $\eta^2 = .020$.

Discussion

This study set out to examine the AI usability perceptions of agricultural engineering students in Turkey, with a particular focus on differences by gender and class year. Before discussing the substantive findings, it is worth noting that the AUAS demonstrated sound psychometric properties in both EFA and CFA, supporting its use as a reliable and valid instrument for measuring AI usability perceptions in agricultural education contexts.

With respect to descriptive findings, the students' overall perceptions were moderately positive, with higher scores on the perceived AI potential subscale than on the perceived barriers subscale. This pattern is consistent with the broader literature on technology acceptance in agricultural education, which suggests that students and young professionals tend to be optimistic about the potential of emerging technologies even while acknowledging practical obstacles to their adoption (Klerkx et al., 2019; Wolfert et al., 2017). The finding that students

scored above the midpoint on the barriers subscale nonetheless warrants attention, as it indicates that issues such as infrastructure deficiency, high costs, and insufficient digital literacy are salient concerns for agricultural engineering students, echoing challenges documented in empirical studies on AI adoption in farming communities (Liakos et al., 2018; Eastwood et al., 2019).

The finding that female students reported significantly higher perceived AI potential than their male counterparts is somewhat counterintuitive given the predominant narrative in STEM education research, which often portrays women as less confident or less positive toward technology (Beyer, 2014). However, an emerging body of literature suggests that these patterns are shifting, particularly in fields where technology is framed as a tool for social good and environmental sustainability rather than as an end in itself (Margolis & Fisher, 2002). Agricultural applications of AI—such as smart irrigation, crop disease detection, and sustainable farming management—may resonate particularly strongly with female students who are drawn to socially and environmentally oriented applications of technology. This interpretation aligns with recent findings from studies in related fields indicating that women in agricultural and environmental sciences tend to hold more enthusiastic attitudes toward technology applications that have clear positive societal impacts (Venkatesh et al., 2003). The absence of a significant gender difference in the barriers subscale suggests that both female and male students are equally aware of the structural and contextual challenges facing AI adoption in Turkish agriculture.

The class year effect observed for the PAP subscale is consistent with the hypothesis that academic experience fosters more positive and nuanced views about AI. As students progress through their agricultural engineering programs, they are likely to encounter more advanced coursework in precision agriculture, crop science, and agricultural technology, which may increase their appreciation of AI's potential contributions. This finding aligns with the educational progression hypothesis advanced in technology integration research, whereby students who have had more exposure to disciplinary content develop more sophisticated views of how emerging technologies can be applied in their field (Kamilaris & Prenafeta-Boldú, 2018; Rogers, 2003). The fact that no class year differences were found for perceived barriers suggests that concerns about AI adoption infrastructure, cost, and digital literacy remain equally salient regardless of academic experience—a finding that points to systemic challenges in agricultural AI adoption that may be resistant to change through coursework alone.

The present findings have several practical implications. First, agricultural education programs should consider explicitly incorporating AI literacy modules across all years of study, rather than limiting such content to advanced courses. Early exposure to AI concepts and applications may help first-year students develop more positive perceptions of AI potential earlier in their academic careers. Second, the gender difference in perceived AI potential suggests that instructors should explore pedagogical approaches that link AI applications to environmental and social sustainability outcomes, which may be particularly motivating for female students. Third, the persistent awareness of barriers across all student groups underscores the need for agricultural education to address not only the technical dimensions of AI but also the economic, infrastructural, and social challenges of AI adoption in Turkish agricultural contexts.

Several limitations of the present study should be acknowledged. First, the use of convenience sampling limits the generalizability of the findings to the broader population of agricultural engineering students in Turkey. Future research should use probability sampling methods to obtain more representative samples. Second, the cross-sectional design of the study precludes causal inferences about the relationship between academic experience and AI perceptions. Longitudinal studies tracking students across their academic careers would provide

stronger evidence for the academic progression hypothesis. Third, the AUAS, while demonstrating sound psychometric properties in the present study, requires additional validation with diverse samples and in other cultural contexts. Finally, the self-report nature of the data introduces the possibility of social desirability bias, particularly for items assessing attitudes toward emerging technologies.

Conclusion

This study examined the AI usability perceptions of 223 agricultural engineering students from two Turkish universities, using the newly developed AI Usability in Agriculture Scale. Overall, students held moderately positive views about the potential of AI in agriculture, while also recognizing significant barriers to its adoption. Female students showed significantly higher perceptions of AI potential than male students, and students' perceived AI potential increased significantly with academic year, particularly from the first to the third and fourth years. These findings contribute to a growing body of literature on technology attitudes in agricultural education and offer practical guidance for educators and policymakers working to foster AI literacy and adoption in agricultural contexts.

Future research should replicate and extend these findings with larger, more representative samples and should explore additional factors that may influence agricultural engineering students' AI perceptions, such as prior coursework in technology, access to digital infrastructure, and exposure to AI applications in practicum settings. As AI continues to transform agricultural systems worldwide, equipping the next generation of agricultural professionals with both the knowledge and the positive attitudes needed to embrace these technologies is more important than ever.

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