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PAPER

# Exploring Behavioral Patterns of Generative AI Usage in Higher Education: A Data-Driven Segmentation Approach

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**ABSTRACT**

This study explores behavioral patterns of generative artificial intelligence (GenAI) usage in higher education using a data-driven segmentation approach. Moving beyond intention-based models such as the technology acceptance model and the Unified Theory of Acceptance and Use of Technology, the study focuses on actual usage behavior and user heterogeneity. Data were collected through a structured questionnaire measuring AI usage behaviors and psychological factors, including trust and AI anxiety. A machine learning–based clustering approach, specifically K-means clustering, was employed to identify user segments, while ANOVA examined differences across clusters. The findings reveal three distinct groups: skeptical users, pragmatic users, and power users, with significant differences in usage frequency, trust, anxiety, and behavioral intention ($p < 0.001$). Notably, power users exhibit both high trust and elevated anxiety, highlighting the complex psychological dynamics of intensive AI usage.

**KEYWORDS**

generative artificial intelligence (GenAI), behavioral patterns, agricultural education, user segmentation, clustering, AI anxiety

## 1 INTRODUCTION

The rapid advancement of generative artificial intelligence (GenAI) technologies has fundamentally transformed how learners access, process, and apply knowledge across disciplines [1, 2]. Tools such as ChatGPT and other AI-powered systems are increasingly integrated into educational contexts, enabling students to perform tasks ranging from information retrieval and content generation to problem-solving and decision support. In agricultural education, where knowledge is often complex, context-specific, and interdisciplinary, GenAI presents new opportunities to enhance learning efficiency, improve decision-making, and support innovation in modern farming practices. Despite the growing adoption of GenAI in higher education,

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limited attention has been paid to how students actually use these technologies in practice. Prior studies largely relied on intention-based models such as TAM and UTAUT; however, these approaches provide limited insight into actual behavioral heterogeneity. This limitation is particularly relevant in the context of GenAI, where usage patterns vary in frequency, purpose, trust, and emotional responses such as AI anxiety. In particular, there remains a lack of empirical evidence on the diversity of user behaviors, usage patterns, and interaction styles with GenAI tools, especially within domain-specific fields such as agricultural education. Prior studies have extensively examined technology adoption in educational contexts using models such as TAM and UTAUT [3, 4].

This limitation is critical because students do not constitute a homogeneous group of technology users. Their engagement with generative AI varies in terms of frequency, purpose, trust, and emotional responses such as anxiety [1, 5]. For instance, some students actively rely on AI tools for problem-solving and knowledge enhancement, while others exhibit cautious or minimal use due to concerns about reliability, misuse, or overdependence [1]. Understanding these behavioral differences is essential for designing effective educational strategies, tailoring AI-supported learning environments, and ensuring responsible and meaningful use of GenAI technologies.

To address this gap, recent studies have begun to adopt data-driven approaches, particularly those grounded in machine learning, to uncover hidden patterns in user behavior [6, 7]. Among these approaches, clustering techniques provide a powerful means of identifying distinct user segments based on observed behavioral characteristics. Such segmentation allows researchers to move beyond aggregate-level analysis and develop a more nuanced understanding of how different groups of students interact with GenAI in practice.

Building on this perspective, the present study aims to explore the behavioral patterns of GenAI usage among agricultural students through a data-driven segmentation approach. Using survey data that captures both usage behaviors and psychological factors, including trust and AI-related anxiety, this study seeks to identify distinct user profiles and examine how these profiles differ in their interaction with GenAI tools. By shifting the focus from intention-based models to actual behavioral patterns, this research contributes to a deeper understanding of AI adoption in educational contexts. The contributions of this study are threefold. First, it advances the literature on GenAI in education by emphasizing behavioral usage patterns rather than solely adoption intention. Second, it introduces a data-driven segmentation approach to identify heterogeneous user groups, thereby extending traditional technology acceptance frameworks. Third, it provides practical insights for educators and policymakers in agricultural education to design targeted interventions that align with the needs and characteristics of different learner segments.

## 2 LITERATURE REVIEW

### 2.1 Generative AI in educational contexts

The emergence of generative artificial intelligence has significantly reshaped contemporary learning environments by enabling students to generate content, synthesize knowledge, and solve complex problems in real time. Unlike traditional digital tools, GenAI systems offer interactive and adaptive capabilities that support personalized learning experiences. Recent studies have highlighted the role of generative AI in supporting personalized learning and cognitive scaffolding [1, 8]. In the context of higher education, these technologies are increasingly used for tasks such as summarizing academic content, generating reports, and assisting with problem-solving across various domains [9, 10]. In agricultural education, the integration of GenAI is particularly promising due to the field's reliance on multidisciplinary knowledge, including biological systems, environmental factors, and technological applications [11, 12]. Students can utilize AI tools to analyze agricultural data, diagnose plant or animal conditions, and access up-to-date information that supports decision-making. However, the adoption and usage of GenAI in this context are not uniform, as students differ in their levels of engagement, trust, and perceived usefulness of such technologies.

### 2.2 Behavioral perspectives on AI usage

Recent research has begun to shift attention from intention-based models to behavioral perspectives that examine how users actually interact with AI technologies [13, 14]. These perspectives consider factors such as frequency of use, task-specific applications, and user strategies in engaging with AI systems. Behavioral usage is especially important in educational contexts, where the effectiveness of technology depends not only on adoption but also on how it is integrated into learning processes. In the case of GenAI, behavioral patterns may include using AI for time-saving purposes, knowledge enhancement, problem-solving, or even substituting independent thinking [15]. Additionally, users differ in their critical evaluation of AI outputs, with some consistently verifying information while others rely on AI responses without validation [16]. These variations highlight the importance of understanding behavioral diversity among users. Moreover, psychological factors play a crucial role in shaping these behaviors [13]. Constructs such as trust influence users' willingness to rely on AI-generated information, while perceived risk may deter usage due to concerns about accuracy and potential negative consequences. Similarly, AI-related anxiety can affect users' confidence and comfort in interacting with AI systems, leading to varying levels of engagement.

### 2.3 Data-driven segmentation and clustering approaches

To better capture heterogeneity in user behavior, recent studies have increasingly adopted data-driven techniques, particularly those based on machine learning. Among these, clustering methods such as K-means have been widely used to identify distinct user segments based on observed characteristics [17, 18]. Unlike traditional variable-centered approaches, clustering enables a person-centered analysis that groups individuals with similar behavioral patterns. In educational research, clustering has been applied to identify different types of learners, engagement styles, and technology usage patterns [19]. This approach is particularly suitable for analyzing GenAI usage, where users may exhibit diverse interaction behaviors that cannot be fully explained by linear relationships alone. By identifying clusters such as frequent users, selective users, and low-engagement users, researchers can gain deeper insights into how different groups interact with AI technologies. Furthermore, clustering results can be enriched by profiling each segment based on psychological and demographic variables. This allows for a comprehensive understanding of not only how users behave but also why such behaviors occur. As a result, data-driven segmentation provides a valuable framework for bridging the gap between behavioral observation and theoretical explanation.

## 2.4 Research gap

Despite the growing interest in GenAI in education, several gaps remain in existing literature. First, most studies continue to rely on intention-based models, with limited attention to actual behavioral patterns of AI usage. Second, there is a lack of research focusing on domain-specific contexts such as agricultural education, where the application of GenAI may differ significantly from other fields. Third, few studies have employed data-driven segmentation techniques to uncover heterogeneity among users, particularly in relation to psychological factors such as trust and AI anxiety. To address these gaps, the present study adopts a behavioral and data-driven approach to explore how agricultural students use GenAI in practice. By integrating behavioral usage data with clustering techniques, this study aims to identify distinct user segments and provide a more nuanced understanding of GenAI engagement in educational settings.

# 3 METHODOLOGY

## 3.1 Research design and sample

This study employed a quantitative, cross-sectional design to examine behavioral patterns of generative AI usage among undergraduate agricultural students in Thailand. Data were collected through a structured questionnaire administered across multiple universities. Convenience sampling was used, with efforts to ensure diversity in academic year, specialization, and location. Participants were required to have prior experience with generative AI tools such as ChatGPT. After data screening and removal of incomplete responses, 224 valid responses were retained for analysis.

## 3.2 Measurement of variables

The questionnaire consisted of three sections: demographic information, behavioral AI usage, and psychological factors. Demographic variables included gender, age, academic year, field of study, and daily technology use. Behavioral AI usage was assessed through indicators reflecting students' engagement with digital technologies and generative AI tools. These indicators included digital learning usage, agricultural digital tool usage, and ChatGPT usage frequency. The measures captured the extent to which students utilized digital technologies and AI-supported tools in their learning activities. Psychological factors were measured to support cluster profiling and interpretation. The constructs included trust in AI, AI anxiety, and behavioral intention. Trust in AI reflects the degree to which students believe AI-generated outputs are reliable and useful. "AI anxiety" refers to feelings of discomfort or apprehension when interacting with AI technologies, while "behavioral intention" reflects students' willingness to continue using generative AI in the future.

## 3.3 Data analysis procedure

Data analysis was conducted in four stages. First, data screening was performed to identify missing values, outliers, and distribution issues, followed by descriptive statistics to summarize respondent characteristics and usage patterns.

Second, composite scores representing digital learning usage, agricultural digital tool usage, and ChatGPT usage were used as behavioral indicators for clustering analysis.

Third, a data-driven segmentation approach using K-means clustering was applied to identify distinct user groups based on behavioral patterns [17, 20]. The optimal number of clusters was determined using the elbow method and silhouette coefficient [21], while cluster validity was assessed through within-cluster homogeneity and between-cluster heterogeneity.

Finally, cluster profiling was conducted using one-way ANOVA and post hoc comparisons to examine differences across groups. Psychological factors, including trust in AI and AI anxiety, were used to interpret the behavioral characteristics of each cluster.

### 3.4 Measurement validation

Prior to clustering, the reliability and validity of the measurement constructs were confirmed using standard criteria. All indicators met the recommended thresholds for internal consistency, convergent validity, discriminant validity, and multicollinearity assessment [17, 22]. Confirmatory factor analysis was conducted prior to clustering to assess the reliability and validity of the measurement constructs. The measurement model assessment results are presented in Table 1.

### 3.5 Post-hoc test and effect size

To further examine between-cluster differences beyond ANOVA, post-hoc comparisons were conducted using Tukey's HSD test.

**Post-hoc results.** Significant pairwise differences were observed across all clusters for key variables ($p < 0.001$), particularly between skeptical users and power users.

**Effect size.** The magnitude of differences was assessed using eta squared ($\eta^2$) [23]. The effect size analysis demonstrates that the differences across clusters are not only statistically significant but also substantively meaningful. Behavioral intention ($\eta^2 = 0.28$) and trust in AI ($\eta^2 = 0.25$) exhibit large effect sizes, underscoring their critical role in distinguishing user segments. AI anxiety shows a moderate effect ($\eta^2 = 0.18$), suggesting a nuanced yet important influence on user behavior. In addition, usage-related variables present medium to large effects ($\eta^2 = 0.20$–$0.30$), indicating that variations in usage patterns are central to understanding user heterogeneity. Overall, these findings confirm the robustness and practical relevance of the identified clusters.

### 3.6 Analytical framework

This study adopts a person-centered analytical approach integrating behavioral indicators with K-means clustering to identify distinct user segments. The overall analytical framework is presented in Figure 1.

### 3.7 Use of AI tools

Artificial intelligence tools were used solely to assist with figure visualization and language editing during manuscript preparation. No AI tools were used for data analysis, interpretation of results, or generation of scientific conclusions. All outputs were critically reviewed by the authors, who retain full responsibility for the accuracy and integrity of the manuscript.

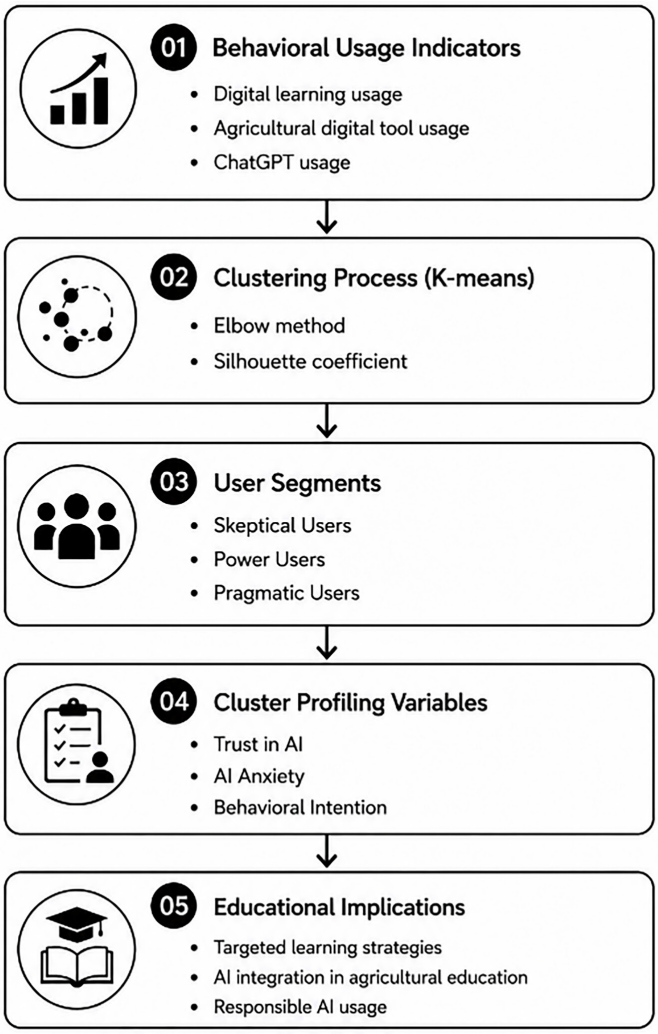


**Fig. 1.** Analytical framework for behavioral usage–driven segmentation and profiling of generative AI users in agricultural education

**Table 1.** Measurement model assessment

| Construct | α | CR | AVE | HTMT (max) |
|---|---|---|---|---|
| Trust in AI | 0.88 | 0.91 | 0.71 | 0.78 |
| AI Anxiety | 0.87 | 0.90 | 0.69 | 0.83 |
| Behavioral Intention | 0.90 | 0.93 | 0.76 | 0.79 |

*Note:* All values meet recommended thresholds (α, CR > 0.70; AVE > 0.50; HTMT < 0.85).

**Table 2.** Descriptive statistics of key variables

| Variable | Mean | SD |
|---|---|---|
| Digital learning usage | 4.37 | 0.85 |
| Agricultural digital tool usage | 2.96 | 1.27 |
| ChatGPT usage | 3.93 | 0.91 |

**Table 3.** Cluster centers (Behavioral segmentation results)

| Variable | Cluster 1 | Cluster 2 | Cluster 3 |
|---|---|---|---|
| Digital learning usage | 3.88 | 4.68 | 4.52 |
| Agricultural tools usage | 2.67 | 4.12 | 2.61 |
| ChatGPT usage | 3.42 | 4.52 | 3.98 |
| Trust in AI | 2.58 | 4.20 | 3.26 |
| AI Anxiety | 2.55 | 3.92 | 3.09 |
| Behavioral intention | 2.76 | 4.28 | 3.67 |

**Table 4.** ANOVA results across clusters

| Variable | F-Value | p-Value |
|---|---|---|
| Digital learning usage | 9.20 | <0.001 |
| Agricultural tools usage | 17.40 | <0.001 |
| ChatGPT usage | 14.85 | <0.001 |
| Trust in AI | 18.72 | <0.001 |
| AI Anxiety | 11.63 | <0.001 |
| Behavioral intention | 21.05 | <0.001 |

**Table 5.** Post-hoc and effect size results

| Variable | Tukey HSD | $\eta^2$ | Interpretation |
|---|---|---|---|
| Digital learning usage | All pairs differ | 0.20 | Medium |
| Agricultural tools usage | All pairs differ | 0.30 | Large |
| ChatGPT usage | All pairs differ | 0.24 | Large |
| Trust in AI | All pairs differ | 0.25 | Large |
| AI Anxiety | Partial differences | 0.18 | Medium |
| Behavioral Intention | All pairs differ | 0.28 | Large |

**Table 6.** Cluster profiles

| Cluster | n (%) | Profile Description |
|---|---|---|
| Cluster 1 | 66 (29.5%) | Skeptical Users: characterized by low AI usage, low trust in AI, and low behavioral intention. |
| Cluster 2 | 50 (22.3%) | Power Users: characterized by high AI usage, high trust in AI, strong behavioral intention, and moderate AI anxiety. |
| Cluster 3 | 108 (48.2%) | Pragmatic Users: characterized by moderate AI usage and balanced perceptions toward AI technologies. |

# 4 RESULTS

## 4.1 Descriptive statistics of behavioral variables

The segmentation results are consistent with the analytical framework presented in Figure 1. Table 2 presents the descriptive statistics of key behavioral variables related to generative AI usage. Students reported high levels of digital learning usage (M = 4.37, SD = 0.85), indicating strong engagement with digital learning environments. Agricultural digital tool usage was moderate (M = 2.96, SD = 1.27), suggesting that domain-specific technology adoption remains less prevalent. ChatGPT usage was relatively high (M = 3.93, SD = 0.91), reflecting the growing integration of generative AI tools into students' learning activities.

## 4.2 Identification of user segments

To explore heterogeneity in AI usage behavior, a K-means clustering analysis was conducted. Based on the elbow method and interpretability considerations, a three-cluster solution was selected as optimal. The clustering results, presented in Table 3, reveal distinct behavioral patterns among students.

Cluster 1 is characterized by relatively low levels of AI usage across most dimensions. Students in this group report limited use of AI tools such as ChatGPT and demonstrate lower levels of trust in AI (M = 2.58) as well as lower behavioral intention (M = 2.76). This group can be interpreted as "skeptical users," who remain cautious and less engaged with generative AI technologies.

Cluster 2 represents students with the highest levels of engagement. This group shows strong usage across all indicators, including frequent use of AI tools (e.g., ChatGPT M = 4.52) and high levels of trust (M = 4.20). Behavioral intention is also the highest among all clusters (M = 4.28), indicating strong willingness to continue using AI in the future. Interestingly, this group also reports moderate levels of AI-related anxiety (M = 3.92), suggesting that intensive usage does not eliminate concerns about AI. This cluster is labeled as "Power Users."

Cluster 3 exhibits moderate levels of AI usage and balanced perceptions across variables. Students in this group use AI tools regularly but not extensively, and their levels of trust and anxiety fall between those of the other two clusters. Behavioral intention is also moderate (M = 3.67), indicating a pragmatic approach to AI usage. This group is identified as "Pragmatic Users."

## 4.3 Differences across clusters

To validate the clustering results, one-way ANOVA tests were conducted to examine differences among the three clusters. As shown in Table 4, significant differences were found across all key variables, including digital learning usage ($F = 9.20$, $p < 0.001$), agricultural tool usage ($F = 17.40$, $p < 0.001$), ChatGPT usage ($F = 14.85$, $p < 0.001$), trust in AI ($F = 18.72$, $p < 0.001$), AI anxiety ($F = 11.63$, $p < 0.001$), and behavioral intention ($F = 21.05$, $p < 0.001$). These findings confirm that the identified clusters are statistically distinct and meaningful. In particular, trust and behavioral intention exhibit the strongest differences across clusters, indicating that these variables play a critical role in differentiating user behavior. Additionally, the significant variation in AI anxiety suggests that emotional responses toward AI are an important factor shaping usage patterns. Post hoc comparisons and effect size analysis further confirmed the robustness of the segmentation results (refer to Table 5).

## 4.4 Behavioral profiles of AI users

Table 6 summarizes the profiles of the three user segments. The results reveal a clear stratification of students based on their engagement with generative AI.

The Skeptical Users (Cluster 1) represent individuals with low engagement, limited trust, and low intention to use AI. This group may require targeted interventions, such as training and awareness programs, to increase confidence in AI technologies.

The Power Users (Cluster 2) demonstrate high engagement and strong reliance on AI tools. However, their relatively high levels of anxiety suggest a nuanced relationship between usage intensity and psychological responses. These findings highlight that even experienced users may remain concerned about the reliability or consequences of AI usage.

The Pragmatic Users (Cluster 3) form the largest group and exhibit moderate engagement. These users appear to adopt AI selectively, balancing its benefits with perceived risks. This group represents a transitional segment that may shift toward either higher or lower engagement depending on future experiences and support.

### 4.5 Key findings

Overall, the results highlight three important insights. First, generative AI usage among agricultural students is heterogeneous, with clear distinctions between low, moderate, and high engagement users. Second, psychological factors such as trust and anxiety significantly differentiate user groups, suggesting that adoption is not solely driven by perceived usefulness or ease of use. Third, the coexistence of high usage and high anxiety among power users indicates a complex behavioral dynamic, where frequent interaction with AI does not necessarily lead to complete confidence. These findings underscore the importance of adopting a behavioral and segmentation-based perspective when examining AI usage in educational contexts.

## 5 DISCUSSION

This study highlights the heterogeneous nature of generative AI usage among agricultural students, demonstrating that actual usage behavior cannot be fully explained by traditional intention-based models alone. By adopting a person-centered clustering approach, the findings reveal three distinct user segments with differing levels of engagement, trust, and anxiety, offering a more nuanced understanding of human–AI interaction in educational settings. Consistent with prior research, psychological factors remain important in shaping technology use. However, unlike earlier studies focused primarily on behavioral intention, this study shows that actual GenAI usage varies substantially across user groups. Notably, the coexistence of high usage and high anxiety among power users suggests that increased familiarity with AI may strengthen both reliance and critical awareness, reflecting the complexity of AI adoption in higher education.

From a practical perspective, the findings suggest that a uniform approach to AI integration may be ineffective. Skeptical users may benefit from foundational training and confidence-building initiatives, while more active users may require guidance on responsible and critical AI use. Institutions should also strengthen the integration of domain-specific AI applications and promote AI literacy that extends beyond technical proficiency. This study has limitations. The use of self-reported data may not fully reflect actual behavior, and the focus on agricultural students may limit generalizability. In addition, clustering identifies behavioral patterns but does not establish causal relationships. Future research should incorporate objective usage data, broader disciplinary contexts, and longitudinal designs to further examine the evolving dynamics of generative AI use.

## 6 CONCLUSION

This study examined generative AI usage among agricultural students using a behavioral, data-driven segmentation approach. The findings reveal three distinct user groups—skeptical users, pragmatic users, and power users—highlighting the heterogeneous nature of AI adoption in higher education. Notably, the coexistence of high usage and high anxiety among power users underscores the complexity of human–AI interaction and challenges the assumption that greater experience necessarily leads to higher confidence. By shifting the focus from behavioral intention to actual usage patterns, this study contributes to a more nuanced understanding of AI adoption in educational contexts. The findings also suggest that educational institutions should adopt differentiated strategies to support effective and responsible AI use. Future research should extend this work across broader contexts and longitudinal settings to better capture the evolving dynamics of generative AI adoption.

## 7 ETHICAL APPROVAL

This study was approved by the Human Research Ethics Committee of Prince of Songkla University (PSU-HREC), Thailand, under approval number **PSU-HREC-2025-105-1-1**.

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