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Research Article

Latent profiles of AI learning conditions among university students: Implications for educational intentions

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ABSTRACT

This investigation aimed to ascertain latent profiles of university students predicated on fundamental factors influencing their intentions to acquire knowledge in artificial intelligence (AI). The study scrutinized four dimensions: supportive social norms, facilitating conditions, self-efficacy in AI learning, and perceived utility of AI. Through the utilization of latent profile analysis (LPA), the investigation endeavored to unveil distinct subgroups of students delineated by unique amalgamations of these factors. The study was carried out with a cohort of 391 university students from diverse academic disciplines. LPA disclosed five unique subgroups of students: Cautious Participants, Enthusiastic Advocates, Reserved Skeptics, Pragmatic Acceptors, and Disengaged Critics. These categories showed somewhat different goals to learn AI; Enthusiastic Advocates showed the highest intention while Disengaged Critics showed the lowest. The findings enhance the growing corpus of research on AI education in higher education by providing a sophisticated knowledge of the variation among university students about their attitudes and preparedness to learn AI. Subgroups of students show that learners need unique educational strategies and interventions to meet their diverse needs and attitudes. AI is changing many fields, therefore college students must learn about it and prepare for it. The findings advance AI education research and impact curriculum and policy.

Keywords: artificial intelligence, higher education, latent profile analysis, situated expectancy-value theory, intention to learn AI

INTRODUCTION

Artificial intelligence (AI) has become an important technology that is transforming various aspects of our lives, including education (Sharma, 2023). With the advancement and proliferation of AI in different fields, it has become critical for university students to acquire AI literacy and skills in order to succeed in an AI-driven future (Southworth et al., 2023). The rapid development of AI applications, especially generative AI tools such as ChatGPT, has led to intense debates in the education community about their potential benefits and challenges in supporting learning processes (Lavidas et al., 2024; Šumak et al., 2024).

AI integration in higher education presents both opportunities and challenges. While AI technologies offer promising advantages in enhancing learning experiences and academic performance, concerns about appropriate application and possible misuse remain. Recent research has highlighted the positive impact of AI applications on students' learning outcomes, especially in areas such as personalized learning, immediate feedback, and research support (Adiguzel et al., 2023). But effective integration of AI into learning environments calls for a thorough awareness of students' attitudes, readiness, and intents to interact with new technologies.

Examining students' motivation and involvement in learning environments (Eccles & Wigfield, 2002, 2020) benefits much from a theoretical framework offered by grounded expectancy-value theory (EBVT). One can choose this idea for some really significant reasons. First, it expands conventional expectancy-value theory (EVT) by stressing the contextual character of motivation and realizing that the particular learning environment shapes people's values and beliefs (Dietrich et al., 2019). Second, in the framework of AI, LBT clarifies how students' engagement and usage habits are influenced by their expectations of performance as well as the apparent value of AI tools (Chai et al., 2020). Third, several studies in the literature have demonstrated the effectiveness of ICBT in explaining technology acceptance and use (Wang et al., 2021; Wu et al., 2022). Finally, the structure of the ICBT, which considers contextual factors, is particularly suitable for studying the acceptance of complex technologies such as AI (Maheshwari, 2024).

Existing research has examined various factors influencing students' adoption of AI technologies in higher education. Empirical research has identified that perceived usefulness, ease of use, and social norms are important predictors of students' intention to use AI-based learning systems (Scherer & Teo, 2019). The recent study by Lavidas et al. (2024) emphasized the importance of understanding the determinants of humanities and social sciences students' intentions to use AI applications, drawing attention to factors such as perceived benefits, social influence and facilitating conditions.

The existing technique has viewed students as a homogenous group, employing analyses such as regression or structural equation modeling (SEM) (Scherer & Teo, 2019; Wang et al., 2021). This is despite the rising corpus of work on AI in higher education. This method ignores the inherent variation that occurs within student populations and ignores the manner in which different combinations of elements could affect different student groupings. Moreover, although previous studies have looked at AI acceptance in many other fields, knowledge on how students in humanities and social sciences interact with AI technologies has stayed lacking. This is particularly noteworthy because AI tools are used in tasks that are particularly important for these fields, such as writing, research, and content analysis (Lavidas et al., 2024; Šumak et al., 2024).

To overcome these limitations, this research uses latent profile analysis (LPA) to identify different subgroups of students based on supportive social norms, facilitating conditions, self-efficacy in AI learning, and perceived usefulness of AI. Given the variety of the student population, the objective of this study is to arrive at a fuller knowledge of how many components interact to influence students' wish to learn AI. The outcomes should enable the development of focused teaching strategies and interventions more suited for the several requirements and traits of various student groups.

Moreover, knowing the characteristics of these groups of students will enable one to provide wise suggestions for customizing instructional resources and services since their relevance in AI research increases. This understanding can help to enable more efficient and entertaining AI education in an environment where AI is growing more and more significant, hence boosting students' learning experiences and results.

THEORETICAL FRAMEWORK

There are several theoretical models to help to understand students' motivations to adopt and exploit AI technologies. Among these, stand out the technology acceptance model (TAM) (Davis et al., 1989), theory of planned behavior (TPB) (Ajzen, 2020), unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003), and situated expectancy-value theory (SEVT) (Eccles & Wigfield, 2020). EBVT was chosen for this investigation for numerous really significant reasons. First, although models like TAM and UTAUT handle technology acceptance in general, EBVT was designed especially in the educational setting and concentrated on knowing students' motivation (Eccles & Wigfield 2020). The educational aspect of EBVT provides a more appropriate theoretical prism through which one could see the acceptability of AI in an academic environment.

Emphasizing the contextual character of motivation, EBVT greatly expands classic EVT. This method acknowledges that the particular environment in which people grow shapes their beliefs and aspirations (Dietrich et al., 2019). This is particularly pertinent for the higher education environment, where the acceptance of AI technologies is influenced not only by individual but also by institutional and social factors (Solórzano-García et al., 2022).

The multidimensional nature of the EBVT better reflects the complex nature of AI acceptance. The theory includes four basic value components: achievement value (the importance of doing a task well), intrinsic value (the enjoyment derived from the task), utility value (the relationship of the task to future goals), and cost (the sacrifices required by the task). This varied approach provides a more whole awareness of the complex factors underlining students' decisions to use AI technology (Chai et al., 2020; Wang et al., 2021).

In the framework of information and communication technology (ICT), students' expectations about AI are investigated in three primary dimensions: self-efficacy beliefs in utilizing AI tools, expectations of success in interacting with AI, and views of technological competency (Maheshwari, 2024; Wu et al., 2022). Moeller et al. (2022) revealed how these expectations shape students' expectations of success in technology use within the dynamics framework. The values dimension, as elaborated by Eccles and Wigfield (2020), encompasses the perceived importance of AI's contribution to academic achievement (achievement value), the intrinsic satisfaction of working with AI (intrinsic value), the benefit of AI skills to future career goals (utility value), and the cost of time and effort involved in learning and using AI (cost value) (Wang et al., 2023). Research bolstering the relevance of these value aspects in students' adoption of technology (e.g., Chai et al., 2020; Wang et al., 2021) point to a comparable impact in the AI setting.

An integral part of the idea includes social and contextual elements. Some of the elements under this category are institutional support and technical infrastructure, norms and expectations inside the educational community (Bouteraa et al., 2024), peer influence and teacher support (Martinot et al., 2022), and academic culture and views on AI (Strzelecki & ElArabawy, 2024). Because of the all-encompassing nature of ICT, it is possible to explore the factors that influence students' decisions to adopt and implement AI technologies in a holistic manner.

This theoretical framework allows us to link the four main dimensions we examined in our research (supportive social norms, facilitating conditions, self-efficacy in AI learning, and perceived usefulness of AI to the core components of EBVT. These aspects enable us to recognize several student profiles in the process of implementing AI technologies and to grasp the particular motivating framework of every profile. The emphasis of the theory on the relevance of personal expectations and ideals as well as social and environmental elements helps one to better grasp the multidimensional character of AI acceptance.

Expectancy-Value Beliefs

The expectancy-value beliefs dimension of SEVT is crucial in understanding students' motivation and engagement when using AI in higher education. According to Eccles and Wigfield (2020) expectancies of success are central drivers influencing students' educational choices, aspirations, and goals. This dimension focuses on students' beliefs (self-efficacy) regarding their ability to succeed in tasks involving AI, impacting their level of engagement and persistence. Value beliefs were measured by the perceived usefulness of AI (Wang et al., 2023). Additionally, the DYNAMICS framework by Moeller et al. (2022) elaborates on the situational expectancy of success within the SEVT. It emphasizes the importance of considering not only the expectancy of success but also various facets of task values, including intrinsic, utility, and attainment values, as well as negative cost values. This framework provides a deeper understanding of how students' perceptions of success and task values influence their motivation and achievement in AI-related activities. In the context of higher education, the integration of AI technologies can significantly impact students' learning experiences. Research by Abgaryan et al. (2023) highlights that AI in higher education benefits students, professors, and administrative staff by enhancing monitoring systems, collaborative learning environments, and research accessibility. When students perceive AI as a tool supporting their learning and academic success, their expectations for success in AI-related tasks are likely to increase. Furthermore, Wu et al. (2022) explore the factors influencing college students' willingness to use AI in learning environments. Understanding these factors is crucial for promoting the effective application of AI in higher education. When students view AI as a valuable resource enhancing their learning outcomes, their expectations for success in tasks involving AI are positively influenced. By considering students' perceptions of success, values associated with tasks, and factors influencing their willingness to use AI, educators and institutions can create supportive environments fostering students' success in utilizing AI technologies for learning.

Supportive Environments

In the context of students using AI in higher education, SEVT plays a crucial role in understanding their behaviors and motivations. SEVT, as proposed by Eccles and Wigfield (2020), encompasses various components that influence students' choices and actions (Kirkham et al., 2023). Specifically, within the supportive environments dimension of SEVT, two sub-dimensions, namely "supportive social norms" and "facilitating conditions," are essential in shaping students' interactions with AI technologies in educational settings (Wang et al., 2023).

"Supportive social norms" refer to the societal expectations and beliefs that influence individuals' attitudes and behaviors towards a particular activity or technology (Strzelecki & ElArabawy, 2024). In the case of students using AI in higher education, social norms can significantly impact their perceptions of AI integration in learning environments. Research has shown that parental expectations, which are a part of social norms, can influence students' perceptions of school and their educational investments (Hascoët et al., 2021). Moreover, the cultural background and social influences, as highlighted in studies related to the acceptance of AI-enabled tools, play a crucial role in shaping students' attitudes towards technology (Jain et al., 2022).

On the other hand, "facilitating conditions" within the SEVT framework pertain to the external factors that can support or hinder individuals in engaging with a particular task or technology (Wang et al., 2023). When it comes to students using AI in higher education, facilitating conditions such as effort expectancy, performance expectancy, and social influence have been identified as key factors influencing the acceptance and use of AI-enabled tools (Jain et al., 2022). Additionally, perceived facilitating conditions, along with other factors like perceived ease of use and perceived usefulness, have been found to impact students' acceptance of mobile learning (m-learning) in higher education (Alyoussef, 2021).

In the realm of AI education, the design of the curriculum is crucial in creating facilitating conditions that support students' engagement with AI technologies. Studies emphasize the importance of considering factors like the TPB in designing AI curriculum to enhance students' intention to learn AI (Chai et al., 2020). Furthermore, the collaborative construction of AI curriculum in primary schools is seen as an effort to respond to policy changes and technological advancements, aligning with the notion of creating facilitating conditions for AI education (Dai et al., 2023).

In summary, within the SEVT framework, the dimensions of "supportive social norms" and "facilitating conditions" are instrumental in understanding students' interactions with AI in higher education. Social norms, including parental expectations and cultural influences, shape students' attitudes towards AI, while facilitating conditions such as effort expectancy and curriculum design play a crucial role in supporting students' engagement with AI technologies in educational settings.

LITERATURE REVIEW

Understanding higher education students' perceptions of AI is crucial in shaping educational practices and curricula to meet the evolving needs of learners. SEVT provides a framework to delve into various dimensions influencing students' views on AI, including supportive social norms, facilitating conditions, self-efficacy in learning AI, perceived usefulness of AI, and intention to learn AI. Research by Chai et al. (2020) emphasizes the importance of considering students' attitudes towards AI, focusing on their perceptions of AI's usefulness, potential for societal benefit, and willingness to engage with AI technology. This highlights the multifaceted nature of students' attitudes towards AI, encompassing not just utility but also ethical considerations and societal impact. Incorporating AI into higher education requires a deep understanding of students' perspectives. Studies like that of Buabbas et al. (2023) shed light on students' positive perceptions towards AI, with a significant majority recognizing the benefits of AI in their careers. This positive outlook underscores the potential for AI to enhance learning experiences and prepare students for future professional endeavors. Additionally, research by Demir and Güraksın (2022) suggests that leveraging AI-assisted teaching methods can enhance students' learning skills by aligning educational content with their perceptions and expectations of AI.

The integration of AI in higher education extends beyond student perceptions to encompass the broader educational ecosystem. Abgaryan et al. (2023) highlight the transformative potential of AI in higher education, emphasizing its benefits for students, professors, and administrative staff. This holistic view underscores the need for collaborative efforts to harness AI's capabilities effectively in enhancing teaching, learning, and administrative processes within academic institutions. Moreover, the study by Mehta et al. (2021) underscores the importance of gauging medical students' knowledge and attitudes towards AI in healthcare, indicating a growing recognition of AI's role in shaping future healthcare practices. Educators play a pivotal role in shaping students' perceptions of AI and fostering a conducive learning environment. Lin et al. (2022) stress the significance of educators in cultivating students' perceptions of AI's utility, suggesting that educators must first instill an understanding of AI's benefits to enhance students' willingness to engage with AI technologies. Furthermore, the study by Wagner et al. (2023) delves into prospective physicians' intentions to use AI in their medical practice, highlighting the intricate interplay between knowledge, beliefs, and experiences in shaping individuals' attitudes towards AI adoption.

The acceptance and utilization of AI among students in higher education are influenced by various factors, including gender and study level. Strzelecki and ElArabawy (2024) explores the moderation effect of gender and study level on students' acceptance of generative AI, emphasizing the need to consider individual differences in promoting AI adoption. Additionally, research by Pucchio et al. (2022) underscores the importance of understanding undergraduate medical students' perceptions of AI and their preferences for AI curriculum delivery, indicating a growing interest in integrating AI education into medical training programs. Innovative teaching approaches that incorporate AI technologies can enhance students' learning experiences and prepare them for AI-driven environments. Mehta et al. (2021) highlight the importance of distinguishing foundational AI concepts from specialized skills in medical education, emphasizing the need for a tailored curriculum that aligns with students' educational needs. Moreover, the study by Kim et al. (2022) underscores the significance of equipping students with the skills to collaborate effectively with AI, fostering critical thinking and decision-making abilities in tandem with AI technologies.

Several studies have investigated the factors that influence students' adoption and acceptance of AI technologies in higher education. Scherer and Teo (2019) found that perceived usefulness, perceived ease of use, and subjective norms were significant predictors of students' intention to use AI-based learning systems. Similarly, Wang et al. (2021) reported that students' expectancies for success and perceived value of AI tools were key determinants of their adoption behavior. The effectiveness of AI in enhancing students' learning outcomes has also been a focus of research. Zawacki-Richter et al. (2019) conducted a systematic review of AI applications in higher education and found that AI-based tutoring systems and personalized learning environments showed promising results in improving students' academic performance. Additionally, Adiguzel et al. (2023) highlighted the potential of AI to provide immediate feedback, adapt to individual learning needs, and support self-regulated learning.

However, the implementation of AI in higher education is not without challenges. Alyahyan and Düştegör (2020) identified privacy concerns, lack of transparency, and the need for technical support as potential barriers to students' acceptance of AI technologies. Moreover, the ethical implications of AI, such as algorithmic bias and the potential for exacerbating educational inequalities, have been raised as concerns (Holmes et al., 2019). To address these challenges, researchers have emphasized the importance of involving students in the design and development of AI tools (Chen et al., 2020). Collaborative learning approaches, where students actively engage with AI technologies as part of their learning process, have been proposed as a means to enhance students' understanding and trust in AI (Mena-Guacas et al., 2023). Furthermore, the role of educators in facilitating students' effective use of AI has been highlighted. Renz and Hilbig (2020) argued that instructors need to develop AI literacy and provide guidance to students on how to critically evaluate and utilize AI tools in their learning. Slimi (2023) and Crompton and Burke (2023) also stressed the importance of integrating AI technologies into the curriculum in a pedagogically meaningful way, aligning with learning objectives and assessment practices.

As AI continues to revolutionize higher education, it is essential to explore students' perceptions and attitudes towards AI to inform educational practices effectively. By leveraging SEVT dimensions such as supportive social norms, facilitating conditions, self-efficacy, perceived usefulness, and intention to learn AI, educators and institutions can tailor AI integration strategies to meet students' evolving needs and expectations. This comprehensive understanding of students' perceptions of AI is pivotal in shaping a future-ready educational landscape that equips learners with the skills and competencies needed to thrive in AI-driven environments. In conclusion, the literature on higher education students' usage of AI in educational settings reveals both opportunities and challenges. While AI technologies have the potential to enhance learning outcomes and provide personalized support, it is crucial to address concerns related to privacy, ethics, and student acceptance. Future research should focus on developing student-centered AI tools, promoting AI literacy among educators and students, and investigating the long-term impact of AI on higher education.

Research Purpose and Gap in Literature

In existing studies that examine the perspectives and attitudes of university students, participants are often treated as a homogeneous group, and analyses such as regression or SEM are commonly employed. However, this approach overlooks the fact that students may vary significantly in terms of their competencies concerning the independent variables. Recognizing this limitation, the present study aims to first classify students based on their levels of the independent variables. Subsequently, the study will investigate whether these resulting classes differ in their intentions to use AI in their activities.

This research addresses a notable gap in the literature by shifting the focus from treating students as a single, undifferentiated cohort to recognizing the heterogeneity within the student population. By doing so, it seeks to provide a more nuanced understanding of how various factors influence students' intentions to use AI. The findings of this study are expected to offer practical insights for curriculum developers and policymakers in the field of AI education. Specifically, the results can inform the development of tailored educational content and personalized services that cater to the diverse needs of students.

Moreover, as the personalization of educational content and services becomes increasingly important in AI studies, understanding the characteristics of these student classes will provide valuable recommendations for customization. This can lead to more effective and engaging AI education, ultimately enhancing students' learning experiences and outcomes.

METHODOLOGY

Sample and Data Collection Tools

The instrument developed by Wang et al. (2023), was utilized in this study (**Appendix A**). The adaptation process followed the procedures outlined in **Figure 1**. Initially, the linguistic adaptation of the scale was carried out. Three language experts were involved in this phase. The first group translated the scale from English to Russian, and the second group back-translated it from Russian to English. The third group,

Figure 1. Adaptation process of the data collection tool (Source: Elaborated by authors)

comprising experts proficient in both languages, reviewed and resolved discrepancies, thereby ensuring the linguistic validity of the scale.

In the second stage, the content validity of the scale was assessed through expert evaluations. Three experts in educational technology and two specialists in AI reviewed the items. They confirmed that the items adequately served the intended purpose of the scale.

In the third stage, a pilot study was conducted to assess the comprehensibility of the scale items by the target group. In the sample selection for the pilot study, 15 university students were selected to represent the target group of the main study. These students were not included in the main study. First, the participants were asked to examine the Russian version of the scale and evaluate the comprehensibility of each item. They were asked to read each item and rate it as "comprehensible", "partially comprehensible" and "incomprehensible". They were also asked to write explanations for the items they found partially comprehensible or incomprehensible and to suggest alternative expressions. Then, one-on-one interviews were conducted with 5 students. In these interviews, they were asked to explain what each item meant in their own words and their examples were recorded. This process allowed for a more in-depth assessment of whether the students understood the items correctly. In addition, opinions were also obtained about the formal features of the scale (font type, font size, page layout, etc.). As a result of the pilot study, all students stated that the scale items were understandable. In one-to-one interviews, it was observed that the students interpreted the items as the researchers intended. The examples and explanations given by the students showed that the statements were correctly understood by the target audience. At the end of this process, it was decided that the scale was linguistically appropriate and the data collection phase could proceed.

In the fourth stage, exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and reliability analyses were conducted. The suitability of the data for factor analysis was evaluated using Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) measure. Bartlett's test of sphericity yielded a Chi-square value of 7,723, degrees of freedom (df) of 190, and a p-value < .001. These results indicate significant correlations among variables, supporting the appropriateness of conducting factor analysis. The KMO measure, with an overall value of 0.944, indicated excellent sample adequacy.

The EFA produced a five-component structure consistent with the original scale. The analysis produced clearly understandable variables by means of maximum likelihood extraction with varimax rotation. Factor loadings displaying significant trends ranging from 0.479 to 0.884 revealed strong correlation between the variables and their related factors.

The objects fell inside the same scale of measurements as the original one. With SN3 showing the greatest loading (0.84) and uniqueness of 0.1563, indicating this item strongly represents the social norms (SN) dimension with strong loadings ranging from 0.544 to 0.884. Loadings for FC dimension varied from 0.479 to 0.780; FC exhibited the greatest loading (0.780) and low uniqueness (0.1629). This implies strong item dependability. With loadings between 0.554 and 0.713, the self-efficacy (SE) dimension showed uniqueness of 0.1895 and greatest loading (0.713). With PU having the highest loading (0.827) and very low uniqueness (0.0844), PU dimension displayed strong loadings from 0.694 to 0.827, therefore suggesting great item quality. At last, the intention (IN) dimension displayed loadings between 0.513 and 0.690; IN had the lowest uniqueness (0.0804) and highest loading (0.690).

With regard to variance explained, the five components taken together explained 73.4% of the overall variance. Factor 1 explained 19.5% of the variance (SS loadings = 3.90; factor 2 added an additional 15.3%). SS loadings distribution of variance implies that although the first element catches the most of the variability, all factors significantly contribute to define the general concept. All dimensions collectively explained 73.4% of the variance.

CFA yielded the following fit indices: CFI = 0.952, TLI = 0.941, SRMR = 0.041, and RMSE = 0.0781 (0.0709–0.0855). For reliability assessment, Cronbach's α and McDonald's ω were calculated for each dimension: SN (Cronbach's α = 0.828, McDonald's ω = 0.833), FC (Cronbach's α = 0.909, McDonald's ω = 0.915), SE (Cronbach's α = 0.908, McDonald's ω = 0.9152), PU (Cronbach's α = 0.963, McDonald's ω = 0.963), and IN (Cronbach's α = 0.900, McDonald's ω = 0.905).

The comprehensive analyses showed that the scale is a valid and reliable measurement tool. When the obtained results are evaluated from a practical point of view, it is seen that the scale items accurately and consistently measure the constructs to be measured. The five-dimensional structure that results in offers a thorough evaluation of the aim to apply AI and related elements. Reliability studies revealed that the scale possesses psychometric qualities capable of generating consistent findings in several contexts and timeframes. Moreover, CFA results confirmed that the structure of the scale corresponds with theoretical expectations. These results imply that one may confidently estimate the intention to employ AI and related variables using the scale.

The participants of this study were volunteer students enrolled at Kazan (Volga region) Federal University. Initially, 400 students participated in the study, and 391 students who completed the questionnaires completely after the data cleaning process constituted the final sample. The demographic distribution of the sample has some restrictions even if this sample size is enough for the intended statistical analysis (Hair et al., 2019). The participants' age distribution exhibits a notable grouping toward young adults. Just 2.8% of the students were 24 years and older; 70.3% were between the ages of 18 and 20, 26.9% were between the ages of 21 and 23. According to the combined statistics, 97.2% of the participants are either 23 years of age or younger. Regarding gender distribution, 25.3% of the sample are men and 74.7% of them are women. This population makeup limits the generalizability of the research somewhat. In particular, adult students, graduate students and male students were underrepresented in the sample. However, this distribution is also compatible with the demographic structure of the university. Research indicates that women are more prevalent in social and human sciences disciplines. For instance, in 2022, women received 62% of bachelor's degrees in the humanities, surpassing their share of all degrees by four percentage points (American Academy of Arts & Sciences, 2024) . In this context, it can be said that the gender distribution in the sample reflects the natural demographic structure of the population rather than sampling bias. However, these demographic limitations should be considered in the interpretation and generalization of the findings.

Data Analysis

In this study, LPA was used to identify different subgroups based on the factors affecting students' AI learning intentions. Prior to the analysis, the normality assumption of the data was examined with the Shapiro-Wilk test and skewness and kurtosis values were checked. The research revealed that all variables had reasonable skewness (between –.862 and –.550) and kurtosis (between –.174 and .394).

Two models–model 1 (equal variances and zero covariances) and model 3 (equal variances and equal covariances) – were investigated in latent profile determination. Various fit indices were used for model

Table 1. Comparison of the models

Model	Class	LogLik	AIC	AWE	BIC	CAIC	CLC	KIC	SABIC	ICL	Entropy
1	1	−2,246	4,508	4,609	4,540	4,548	4,494	4,519	4,514	−4,540	1.0000
1	2	−2,002	4,031	4,197	4,083	4,096	4,007	4,047	4,041	−4,096	0.9430
1	3	−1,856	3,748	3,980	3,820	3,838	3,714	3,769	3,763	−3,901	0.8220
1	4	−1,784	3,613	3,909	3,704	3,727	3,569	3,639	3,631	−3,774	0.8550
1	5	−1,756	3,569	3,929	3,680	3,708	3,515	3,600	3,591	−3,757	0.8660
1	6	−1,738	3,543	3,968	3,674	3,707	3,478	3,579	3,569	−3,761	0.8680
3	1	−1,834	3,696	3,876	3,752	3,766	3,670	3,713	3,708	−3,752	1.0000
3	2	−1,834	3,706	3,952	3,782	3,801	3,669	3,728	3,721	−4,134	0.0987
3	3	−1,783	3,613	3,922	3,708	3,732	3,567	3,640	3,632	−3,805	0.7756
3	4	−1,759	3,576	3,949	3,691	3,720	3,520	3,608	3,599	−3,772	0.8381
3	5	−1,749	3,566	4,004	3,701	3,735	3,499	3,603	3,593	−3,837	0.7783
3	6	−1,722	3,522	4,025	3,677	3,716	3,446	3,564	3,553	−3,843	0.7727

comparison. Bayesian information criterion (BIC) was first considered for model selection, followed by Akaike information criterion (AIC), log-likelihood (LogLik), entropy and other fit indices. The five-class solution of model 1 was identified as the optimal model with the lowest BIC value (3,680) and the highest entropy value (0.866). The following criteria were effective in the selection of this model:

1. Lower BIC value compared to other models (3,680).
2. Entropy value is acceptably high (0.866).
3. Classes are theoretically meaningful and interpretable.
4. The number of students in each class is large enough for statistical analysis.

Each of the five classes identified by the LPA showed unique patterns in terms of four key variables (social norms, facilitating conditions, self-efficacy and perceived utility). In naming the classes, the characteristics of each group in terms of these variables and its comparative position with other groups were considered. This naming process was carried out to reflect the characteristics of each group, considering the relationships between variables and differences between groups. The group names was chosen to reflect the dominant characteristics of the group and its comparative position with other groups.

Welch ANOVA test was applied to examine whether the five classes differed in terms of AI learning intentions. This test was selected since the homogeneity of variance between groups proved not to be fulfilled. Pairwise comparisons between groups were done using Games-Howell post-hoc test in line with ANOVA outcomes. This test was chosen because, particularly in cases of unequal sample sizes and variances, it offers consistent findings.

Jamovi program (version 2.5.3) was used in all statistical tests. Beginning with data cleaning and preparation and working methodically through model selection, profile identification, and group comparisons, the analytical procedure Analysis assumptions were examined at every level and required changes were made.

FINDINGS

In choosing the most suitable model and class for LPA, it's crucial to assess several statistical criteria to ensure an optimal balance between model fit and complexity. Upon reviewing **Table 1**, model 1, class 5 emerges as a particularly strong candidate. This model boasts the lowest BIC value of 3680 among all classes in model 1, which is indicative of an effective balance between model fit and the number of parameters, crucial for avoiding overfitting. Additionally, this class has comparatively low values in both the AIC and the sample-size adjusted BIC (SABIC), suggesting a robust model with justifiable complexity. Notably, the entropy value of 0.866 for this class points to a high degree of certainty in the classification, affirming clear differentiation among profiles. Given these metrics–lower AIC, BIC, SABIC, alongside high entropy–model 1, Class 5 stands out as a parsimonious and interpretable option that efficiently captures distinct groupings within the data without unnecessary complexity.

The averages of the variable's social norms, facilitating conditions, self-efficacy and perceived usefulness were examined based on the 5-class model (**Figure 2**).

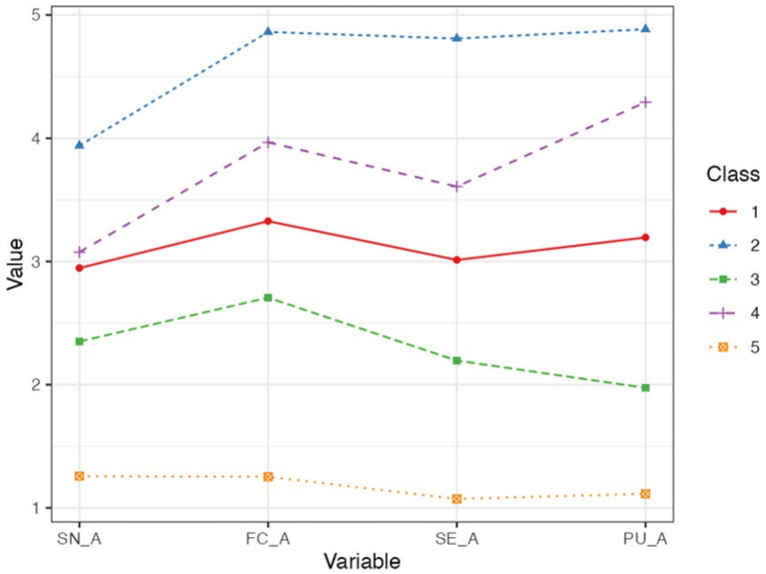

Figure 2. Chart average of independent variables based on the classes (SN_A: Average of social norms; FC_A: Average of facilitating conditions; SE_A: Average of the self-efficacy; PU_A: The average of perceived usefulness) (Source: Elaborated by authors)

Table 2. Mean and ANOVA test results

Class	N	Mean	SD	SE	F	df1-df2	p-value
Cautious participants	108	3.00	0.619	0.0596	368	4.0-87.7	< .001
Enthusiastic advocates	69	4.60	0.558	0.0672			
Reserved skeptics	25	2.23	0.946	0.1893			
Pragmatic acceptors	169	3.65	0.648	0.0499			
Disengaged critics	20	1.15	0.297	0.0664			

Class 1, termed *cautious participants*, shows moderate engagement across all variables. Members of this class participate in activities related to AI but maintain a cautious approach, reflected by their moderate scores in support, facilitation, self-efficacy, perceived usefulness, and interest. This group seems to be tentatively exploring the potential of AI without fully committing to its promise or benefits.

Class 2, identified as *enthusiastic advocates*, stands out with very high scores, particularly in facilitating conditions, self-efficacy, and perceived usefulness. This class represents individuals who are highly supportive of AI, confident in their ability to use and learn AI technologies and see significant benefits in its adoption. Their enthusiasm is likely to drive them to advocate for broader AI integration and utilization.

Class 3, called *reserved skeptics*, scores generally low across all factors but are not the most negative group. This class is characterized by a reserved or cautious skepticism towards AI. While they acknowledge some aspects of AI, their engagement is limited, reflecting significant reservations about AI's efficacy and relevance to their needs.

Class 4, named *pragmatic acceptors*, generally exhibits above-average scores, especially in perceived usefulness and interest in AI. Individuals in this class pragmatically accept AI as a useful and beneficial tool, supported by adequate self-efficacy and facilitating conditions. Their practical acceptance suggests a recognition of AI's value, even if they are not as passionate as the enthusiastic advocates.

Class 5, termed *disengaged critics*, shows very low engagement across all variables, indicating a profound disinterest and critical stance toward AI. This group perceives little usefulness, has minimal self-efficacy, and shows almost no interest in AI, reflecting a deep-seated resistance or disconnection from AI technologies.

Intention to Learn AI-Based on the Classes

Table 2 offers a detailed view into the varying intentions of different classes to learn AI, as identified through LPA. Each class demonstrates distinct levels of interest in AI, as evident from their mean scores, and these differences are statistically significant as indicated by the ANOVA outcomes. The *cautious participants*

Table 3. Games-Howell post-hoc test

		Cautious participants	Enthusiastic advocates	Reserved skeptics	Pragmatic acceptors	Disengaged critics
Cautious participants	Mean difference	-	–1.600***	0.775**	–0.649***	1.850***
	p-value	-	< .001	0.004	< .001	< .001
Enthusiastic advocates	Mean difference		-	2.371***	0.948***	3.450***
	p-value		-	< .001	< .001	< .001
Reserved skeptics	Mean difference			-	–1.424***	1.080***
	p-value			-	< .001	< .001
Pragmatic acceptors	Mean difference				-	2.500***
	p-value				-	< .001
Disengaged critics	Mean difference					-
	p-value					-

consist of 108 individuals and exhibit a moderate intention to learn AI, with a mean score of 3.00. The standard deviation of 0.619 indicates relatively consistent sentiments within this group, albeit with some variation, suggesting a general openness yet cautious approach towards AI learning. *Enthusiastic advocates*, numbering 69, display a strong inclination towards AI, reflected by a high mean score of 4.6. The fairly uniform agreement within this group (standard deviation [SD] = 0.558) points to a homogeneous and positive attitude towards embracing AI technologies.

In contrast, the *reserved skeptics* show much lower enthusiasm, with a mean score of 2.23 and a significantly higher standard deviation of 0.946 among its 25 members. This greater variability indicates a mix of disinterest and skepticism towards AI within the group, underscoring the diverse levels of apprehension or doubt present. The largest group, *pragmatic acceptors*, includes 169 individuals who generally view AI favorably, as evidenced by a mean score of 3.65. Their lower standard deviation of 0.648 suggests that while their interest is positive, it's tempered with practical considerations about AI's applications and benefits. Lastly, the *disengaged critics* are the most uniform in their stance, albeit negatively so. This smallest group (20 individuals) has the lowest mean score of 1.15 and a low standard deviation of 0.297, highlighting a consistent and strong disinterest or critical view towards AI.

The one-way ANOVA results reinforce these observations, with a high F-statistic of 368 and a p-value of less than .001, confirming that the variations in intentions across these classes are statistically significant. These findings validate the effectiveness of the LPA in differentiating groups based on their attitudes and readiness to engage with AI. This segmentation provides valuable insights for developing targeted educational or promotional strategies aimed at fostering AI literacy tailored to the specific needs and attitudes of each group.

Table 3 presents the results of the Games-Howell post-hoc test, applied to compare the mean differences in the intention to learn AI among different classes as determined by LPA. Each value is accompanied by statistical significance, helping to elucidate where the notable differences lie between the groups. *Cautious participants* show significant differences when compared to other classes. Their intention to learn AI is notably lower than that of the *enthusiastic advocates* by an average difference of –1.60 ($p < .001$), indicating a much stronger inclination towards AI in the latter. Conversely, *cautious participants* have a higher intention than the *disengaged critics* by 1.85 ($p < .001$) and *reserved skeptics* by 0.775 ($p = 0.004$), but less than *pragmatic acceptors* by –0.649 ($p < .001$).

Enthusiastic advocates demonstrate the highest intention to learn AI, with significant differences across all groups. They surpass the *reserved skeptics* by 2.371 ($p < .001$), *pragmatic acceptors* by 0.948 ($p < .001$), and the *disengaged critics* by a substantial margin of 3.45 ($p < .001$). *Reserved skeptics* have a significantly lower intention than *enthusiastic advocates*, and also less than the *disengaged critics* by –1.424 ($p < .001$). However, they exhibit a higher intention compared to the *pragmatic acceptors* by 1.08 ($p < .001$).

Pragmatic acceptors are generally more inclined than *cautious participants* and significantly more than the *reserved skeptics*. They also show a notable difference when compared to *disengaged critics*, with an average difference of 2.50 ($p < .001$). *Disengaged critics* rank as having the least intention to engage with AI, showing significant negative differences compared to all other classes. This underlines their critical or disengaged perspective towards learning AI.

Overall, the Games-Howell post-hoc analysis reveals significant distinctions among the classes in terms of their intention to learn AI. The data provides a clear view of how different attitudes and readiness levels cluster within these groups, highlighting both the enthusiasm spectrum and the challenges in engaging certain segments with AI education and integration.

DISCUSSION

The present study aimed to identify distinct subgroups of university students based on their perceptions of supportive social norms, facilitating conditions, self-efficacy in learning AI, and perceived usefulness of AI, and to examine how these subgroups differ in their intentions to learn AI. By employing LPA, the study revealed five distinct classes of students: cautious participants, enthusiastic advocates, reserved skeptics, pragmatic acceptors, and disengaged critics. These findings provide valuable insights into the heterogeneity of students' attitudes towards AI and their readiness to engage with AI education.

The acceptance of these several categories conforms to the SEVT model, which emphasizes the part values and expectations play in defining individuals' drive and actions (Dietrich et al., 2019; Eccles & Wigfield, 2002). The Enthusiastic Advocates class shows strong expectations for success and perceived value in learning AI by means of high scores in favorable conditions, self-efficacy, and perceived usefulness. High self-efficacy and supportive circumstances help these people to embrace AI, therefore displaying a strong learning purpose. Based on the "value" component of SEVT, this suggests a strong motivation; this group clearly sees rather high possible benefits from AI. This result is compatible with previous studies implying that students' adoption behavior is mostly defined by their values and expectations (Wang et al., 2021). Technologies based on AI are used by university students in search and analysis, assignment and report preparation, picture creation in Aleshkovski et al. (2024) survey, students thus demonstrate significant pleasure using AI. Conversely, the disengaged critics class shows low expectancies and perceived benefit in studying AI by scoring poor on all criteria. Towards AI, this category has low "value" and "expectancy". Their attitude toward AI is critical and they clearly lack interest in it. This suggests a strong view of the "cost" of AI or a view that AI does not match their demand in the SEVT paradigm. This corresponds with the idea that both personal and social elements shape students' drive to apply AI (Bouteraa et al., 2024; Strzelecki & ElArabawy, 2024). The discovery of this class emphasizes the need of addressing the issues and obstacles that can prevent students' participation with AI education (Alyahyan & Düştegör, 2020).

The group of cautious participants approaches AI with great care. In the SEVT setting, this might be understood as ambivalence or low self-confidence between the "expectation" and "value" components. Though they see the benefits of AI, cost or uncertainty factors seem to limit this participation. The reserved skeptics class has weak aspects related to "expectation" and "value". There is minimal involvement in the benefits of AI due to questions. This group emphasizes the "cost" portion of SEVT more since they believe that the prospective risks or challenges of investing in AI outweigh the benefits. The findings of Al-Abdullatif and Alsubaie (2024) research indicate that ongoing use depends much on internal motivation and satisfaction. Wang and Li (2024) claim that long-term usage intentions depend much on happy feelings.

The study also emphasizes how important encouraging social norms and facilitating conditions are for determining students' willingness to learn AI. With above-average ratings in perceived usefulness and interest in AI, the Pragmatic Acceptors class points to the need of giving students enough tools and assistance to help them to embrace AI technology. This group does not show great excitement even if they consider AI to be valuable. Although the component of "value" is strong, their "expectation" or dedication toward AI is more realistic. This pragmatic perspective implies that although they understand the value of AI, they are more wary to personally make investments in it. This outcome is in line with previous research stressing the significance of curriculum design in creating acceptable surrounds for AI instruction (Chai et al., 2020; Dai et al., 2023; Lavidas et al., 2024) and the part of pleasant settings in motivating the acceptance of AI-enabled equipment (Jain et al., 2022; Lavidas et al., 2024).

Moreover, the study exposes notable variations in the will to learn AI among the found categories. The enthusiastic advocates exhibited the most intention; the disengaged critics showed the least. These results highlight the requirement of customized instructional plans and interventions to meet the various needs and opinions of students about AI. As advised by Lin et al. (2022), teachers are quite important in helping kids to see the value of AI and to be ready to interact with AI technologies.

When the “AI learning intentions” of these different groups are analyzed within the SEVT framework, it is seen how the “value” and “expectation” components determine the learning intentions of each group. Enthusiastic advocates show the highest learning intentions due to their high “expectancy” and “value” levels, while disengaged critics have the lowest learning intentions due to their low “expectancy” and “value” levels. The objectives of pragmatic acceptors and cautious participants are more in accord with reality, although they are more modest. Based on the findings of Chan and Zhou (2023) and Yurt and Kasarci (2024), it is believed that AI adoption is a crucial factor.

Customized training sessions for many companies filing applications for SEVT in view of these revelations are absolutely vital. Groups like enthusiastic advocates could get advanced instruction and support. On the other hand, groups like reserved skeptics and disengaged critics could be convinced to change their opinions on AI by offering materials that are more basic and appealing and that more precisely show the advantages.

The results of this study contribute to the growing body of literature on AI education in higher education. By employing LPA, the study provides a nuanced understanding of the heterogeneity among university students in terms of their attitudes and readiness to learn AI. This approach addresses a notable gap in the literature, which often treats students as a homogeneous group (Scherer & Teo, 2019; Wang et al., 2021).

The findings have practical implications for curriculum developers, educators, and policymakers in the field of AI education. By identifying distinct subgroups of students, the study offers insights for developing personalized educational content and support services tailored to the specific needs and attitudes of each group. This can lead to more effective and engaging AI education, ultimately enhancing students’ learning experiences and outcomes (Kim et al., 2022; Mehta et al., 2021).

This study provides valuable insights into the heterogeneity of university students’ attitudes and intentions towards learning AI. By identifying distinct subgroups of students, the study highlights the need for tailored educational strategies and interventions to cater to the diverse needs and attitudes of students. The findings contribute to the growing body of literature on AI education and have practical implications for curriculum development and educational policy. As AI continues to transform various domains, it is crucial to foster AI literacy among university students and equip them with the necessary skills and knowledge to thrive in an AI-driven future.

CONCLUSION

This study employed LPA to identify distinct subgroups of university students based on their perceptions of supportive social norms, facilitating conditions, self-efficacy in learning AI, and perceived usefulness of AI. The analysis revealed five classes of students: cautious participants, enthusiastic advocates, reserved skeptics, pragmatic acceptors, and disengaged critics. These classes exhibited significant differences in their intentions to learn AI, with enthusiastic advocates demonstrating the highest intention and disengaged critics showing the least.

The findings contribute to the growing body of literature on AI education in higher education by providing a nuanced understanding of the heterogeneity among university students in terms of their attitudes and readiness to learn AI. The study highlights the importance of considering the diverse needs and attitudes of students when developing AI education strategies and interventions. The results suggest that tailored educational content and support services, catering to the specific characteristics of each subgroup, can lead to more effective and engaging AI education.

The study contains certain really significant restrictions. The demographic structure of the sample first restricts the generalizability of the research. The generalizability of the results to other demographic groups is limited by the fact that most of the participants–74.7%–are female students and that the age distribution is concentrated in the 18–23 range (97.2% of the participants). In particular, the underrepresentation of adult students, graduate students and male students in the sample is an important limitation. In addition, the fact that the data is self-reported and collected from a single university also limits the generalizability of the results. The cross-sectional character of the study makes it impossible to investigate over time the changes in students' views and intentions regarding AI learning.

These limitations lead one to make the following recommendations for future studies: Examined should be the variations in attitudes toward AI learning among different departments, colleges, and demographic groupings. In particular, comparative studies should be conducted including graduate students, adult learners and students from different disciplines. In addition to self-report scales, objective measurement tools should be developed to assess students' AI competencies and learning outcomes. Longitudinal studies should be conducted to investigate the change in students' attitudes and intentions towards learning AI over time and the factors affecting this change. Qualitative research should be conducted deeper on the specific needs and learning preferences of every student profile: Cautious participants, enthusiastic advocates, reserved skeptics, pragmatic acceptors and disengaged critic

Recommendations for practitioners: Every student profile should be represented in customized AI courses and support systems, advises practitioners. For cautious participants, for instance, a step-by-step curriculum emphasizing the fundamental ideas of AI may be developed. For enthusiastic advocates, there are enhanced learning opportunities including advanced applications. Teaching methods stressing the practical advantages and real-world uses of AI should be embraced for abstaining skeptics and indifferent critics. Continuous professional development programs should be organized to improve the AI literacy of lecturers. Establish industry collaborations to provide students with real-world experiences and demonstrate the practical applications of AI in different fields. Mentoring and peer support programs should be created to address the needs of each student profile.

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Data availability: Data generated or analyzed during this study are available from the authors on request.

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APPENDIX A: UNIVERSITY STUDENTS' INTENTIONS TO LEARN AI

Supportive Social Norms

1. *SN1. My university organizes enrichment lessons for me to learn more about AI.*
2. *SN2. My parents encouraged me to participate in innovative AI learning activities.*
3. *SN3. My teachers expect me to learn more about AI technology.*
4. *SN4. My classmates feel that it is necessary to learn how to work on AI technology.*

Facilitating Conditions

1. *FC1. I can gain access to information about AI easily.*
2. *FC2. I can continuously improve my AI knowledge from many open sources.*
3. *FC3. I can easily find help when I need to know more about AI technology.*
4. *FC4. I can download many AI applications to test their efficacy.*

Self-Efficacy in Learning AI

1. *SE1. I am certain I can understand the most difficult material presented in the AI class.*
2. *SE2. I feel confident that I will do well in the AI class.*
3. *SE3. I am confident I can learn the basic concepts taught in the AI class.*
4. *SE4. I believe that I can succeed if I try hard enough in the AI class.*

Perceived Usefulness of AI

1. *PU1. Using AI technology enables me to accomplish tasks more quickly.*
2. *PU2. Using AI technology improves my performance.*
3. *PU3. Using AI technology increases my productivity.*
4. *PU4. Using AI technology enhances my effectiveness.*

Intention to Learn AI

1. *IN1. I will continue to learn about AI technology in the future.*
2. *IN2. I will pay attention to emerging AI applications.*
3. *IN3. I expect that I will be concerned about AI development in the future.*
4. *IN4. I plan to spend time learning AI technology in the future.*