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Exploratory survey on factors influencing the adoption of AI by university students

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Abstract: This study explores the use and acceptance levels of Generative Artificial Intelligence in two groups of Bachelor degree students enrolled at the University of Salerno in General Education Sciences and Motor, Sports and Psychomotor Education Sciences. Through an extension of the Unified Theory of Acceptance and Use of Technology (UTAUT) model, the investigation examines the influence of a series of constructs that include, among others, Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions on Behavioral Intentions, and the tendency to use AI systems when studying. As highlighted in the report published by Save the Children, a growing percentage of adolescents use AI not only for informational purposes, but also for emotional and decision-making support, signaling an increasingly integrated relationship between young people and algorithmic agents. This data and literature reporting concerns regarding the use of AI and inclusion, calls for a broader pedagogical debate to rethink learning beyond an isolationist view of the mind and a reflection on how to educate students in the conscious and critical use of AI systems. In this perspective, this study utilizes an extended UTAUT model that is not limited to measuring the acceptance of technology but may contribute to outlining useful guidelines for the construction of a "radically extended" pedagogy, capable of critically and consciously integrating generative AI into contemporary educational practices.

Keywords: Artificial Intelligence; UTUAT; inclusive education.

1. Introduction

The ubiquitous use of generative artificial intelligence (AI) systems is profoundly reshaping education at policy and practice levels. Curriculum development, instructional design, assessment processes, students' study methods, personalization and learning support, and career guidance are only some examples where AI advancement has already been reported (Zhang & Aslan, 2021). From an inclusive education perspective, a plethora of literature published in the last few years has highlighted both benefits and threats of AI, raising crucial questions about equity in learning opportunities, access to reliable information, teacher agency, and autonomy (Mouta et al.,

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2023). Generative AI tools, especially those based on large language models, are increasingly used by students as cognitive and metacognitive supports for information retrieval, text production, planning, and problem solving, potentially functioning as individualized scaffolds that adapt to diverse learning needs (Kasneci et al., 2023; Zawacki-Richter et al., 2019). Such characteristics resonate with core principles of inclusive pedagogy, which emphasize responsiveness to learner variability and the removal of barriers to participation (Ainscow, 2020; Florian & Black-Hawkins, 2011).

Within inclusive education frameworks, technologies are not considered neutral tools but mediating artifacts that can either widen or reduce educational inequalities depending on how they are designed and used (Selwyn, 2016; Zawacki-Richter et al., 2019). Generative AI has the potential to support inclusive learning by offering flexible explanations, alternative representations of content, and adaptive feedback. These elements align with the principles of Universal Design for Learning (UDL), which advocate multiple means of engagement, representation, and action (CAST, 2018). However, these affordances can only be realized if learners perceive AI as meaningful, trustworthy, and pedagogically relevant. For this reason, understanding students' acceptance of AI becomes a central issue not only for technological innovation, but also for the development of inclusive learning environments. This is particularly salient in degree programs related to education and pedagogical sciences. Students enrolled in such programs are future professionals who will be responsible for designing inclusive learning contexts and plans for pupils with diverse educational needs. Their current experiences with AI as learners, are likely to shape their future professional beliefs, attitudes, and practices (Biesta, 2015; Florian, 2019). Recent studies indicate that pre-service teachers and education students often approach AI with a combination of curiosity and concern, recognizing its potential to support differentiation while simultaneously expressing ethical and pedagogical apprehensions related to over-reliance, bias, and loss of professional judgment (Andrews et al., 2021; Holmes et al., 2022).

To investigate these dynamics, research on technology acceptance offers a valuable theoretical lens. Among existing models, the Unified Theory of Acceptance and Use of Technology (UTAUT) has proven particularly effective in explaining individuals' adoption of digital tools across educational contexts (Venkatesh et al., 2003; Venkatesh et al., 2012). The model identifies Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions as key determinants of behavioral intention. In inclusive education contexts, these constructs take on specific meanings to investigate whether: technology really supports learning diversity; ease of use influences accessibility; facilitating conditions reflect institutional commitment to inclusion; social influence shapes norms around ethical and pedagogically appropriate use.

Subsequent extensions of the UTAUT model have incorporated motivational and affective dimensions, such as Intrinsic Value and Attitude Toward Use, which are especially relevant in inclusive and learner-centered environments where technology adoption is voluntary and meaning-oriented rather than compliance-driven (Khechine et al., 2020). Positive attitudes and intrinsic motivation are widely recognized in inclusive pedagogy as prerequisites for sustained engagement and reflective practice, particularly when innovative tools challenge traditional teaching roles (Florian & Spratt, 2013; Teo, 2019). Empirical studies applying UTAUT to artificial intelligence in higher education suggest that students' acceptance of generative AI is primarily driven by perceived usefulness and positive attitudes, while social influence tends to play a more marginal role (Raza et al., 2022; Wong et al., 2023). Nevertheless, evidence remains fragmented with regard to education-focused degree programs and to students at different stages of their academic trajectory. Moreover, few studies explicitly interpret technology acceptance through an inclusive education lens, despite the growing relevance of AI for differentiated instruction and support planning.

Against this background, the present exploratory study investigates university students' acceptance of generative AI through an adapted UTAUT framework, explicitly situated within an inclusive education perspective. It examines how first-year students in Sport and Psychomotor Education Sciences and third-year students in Educational Sciences perceive different determinants of AI adoption, including usefulness, ease of use, attitudes, and intention to continue using AI tools. The study is embedded within a broader research initiative conducted at the Teaching Learning Centre for Education and Inclusive Technologies – Elisa Frauenfelder Laboratory (University of Salerno), which explores the pedagogical potential of a generative chatbot based on a Retrieval-Augmented Generation (RAG) architecture as a dialogic and dynamic scaffolding tool. By foregrounding students' perceptions, this study aims to contribute to a more nuanced understanding of how generative AI can support inclusive practices in education.

2. Methodology

2.1. Objective

The present exploratory study aims to describe the average level of acceptance of AI, but also to verify whether and how the different constructs of the extended UTAUT model are perceived differently among first-year students in Sport and Psychomotor Education Sciences (L-22) and third-year students in Educational Sciences (L-19) of the University of Salerno.

The research is part of an ongoing project at the Teaching Learning Centre for Education and Inclusive Technologies – Elisa Frauenfelder Laboratory (University of Salerno) that investigates the potential of a generative chatbot, developed using a Retrieval-Augmented Generation (RAG) architecture, as a dialogic and dynamic scaffolding tool to support teachers, such as in designing Individualized Educational Plans (IEPs) and adapting inclusive activities (Zappalà et al., 2025).

2.2. Instrument

The instrument employed in this study was a questionnaire consisting of two sections. The first section collected demographic information as well as data on participants' use and frequency of use of digital tools and GAI. The second section comprised an adapted version of the Unified Theory of Acceptance and Use of Technology (UTAUT) questionnaire, specifically tailored to investigate university students' use of artificial intelligence tools for academic purposes. This adaptation was based on the original scales developed by Venkatesh et al. (2003) and Venkatesh et al. (2012), as well as on subsequent adaptations proposed by Khechine et al. (2020) and previous studies in the fields of teacher education and technology integration (Andrews, Ward & Yoon, 2021).

The questionnaire measured the core UTAUT constructs using multiple Likert-type items rated on a five-point scale (1 = strongly disagree to 5 = strongly agree). According to the UTAUT model (Venkatesh et al., 2003), five main constructs influence individuals' intentions to use technology: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC) and Behavioral intention (BI). Performance Expectancy refers to the degree to which an individual believes that using technology will enhance their performance in completing tasks or achieving goals. Effort Expectancy represents an intrinsic factor related to users' perceptions of the ease of use and comfort associated with technology, which influences their intention to adopt and continue using it. Moreover, previous research has identified a direct causal relationship between Effort Expectancy and behavioral intention to adopt technology (Raza et al., 2022). Social Influence reflects the extent to which individuals perceive that significant others (such as peers, teachers, or friends) encourage or expect them to use a given technology. Finally, Facilitating Conditions refers to users' perceptions of the availability of organizational, technical and infrastructural resources within their environment that support the adoption and effective use of technology (Venkatesh et al., 2003). Behavioral Intention (BI) is defined as the degree to which an individual has shaped conscious plans to perform a specified behavior in the future.

Later extensions of the UTAUT model introduced a seventh construct that is particularly relevant in educational contexts: Intrinsic Value, defined as the enjoyment, interest, or satisfaction derived from using technology (Khechine et al., 2020). In addition, Attitude Toward Using refers to individuals' evaluative and affective responses, encompassing positive feelings, negative reactions and apprehension toward the use of artificial intelligence and related technologies in learning and information environments (Andrews, Ward & Yoon, 2021).

Considering all these constructs, an adapted version of the UTAUT questionnaire was employed in the present study to reflect the university learning environment and to examine the following dimensions of students' use of artificial intelligence:

Constructs	**Definition and example**
Performance Expectancy (PE)	This construct assesses whether students believe that the use of AI improves the quality and outcomes of their academic work. Example item: "Using artificial intelligence will allow me to achieve better results in my studies."
Effort Expectancy (EE)	This dimension measures students' perceptions of the ease of learning and using AI tools. Example item: "Learning to use artificial intelligence is easy for me."
Social Influence (SI)	This construct evaluates the extent to which teachers, peers, and the academic institution encourage the use of AI. Example item: "My classmates think that using artificial intelligence tools is useful."

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Facilitating Conditions (FC)	This dimension assesses whether students perceive that they have the necessary resources, knowledge, and support to use AI effectively. Example item: "I have the resources necessary to use artificial intelligence tools for studying."
Attitude Toward Using (ATU)	This construct captures students' affective reactions toward AI, including both positive evaluations and apprehension (with some items reverse-scored). Example item: "I have a positive attitude toward using artificial intelligence to improve my learning."
Behavioral Intention (BI)	This dimension reflects students' willingness and readiness to use AI tools in their academic activities. Example item: "I feel comfortable interacting with artificial intelligence systems."
Intrinsic Value (IV)	This construct assesses students' long-term interest, enjoyment, and commitment to using AI, including their intention to continue using it and recommend it to others. Example item: "I intend to continue using AI tools in my studies."

2.3. Sample

The sample comprised 150 undergraduate students (65% males, n = 98, and 35% females, n = 52) enrolled in two degree programs at the University of Salerno: 92,2% are first-year students in Sport and Psychomotor Education Sciences (L-22) and 7,8% are third-year students in Educational Sciences (L-19). This composition allowed the study to include both students at the beginning of their academic pathway and those with more advanced university experience. The age distribution is concentrated in the 18-22 years old range, with the largest group being 19-year-old students (46%; n = 69). Only a small minority were older than 24 years (1,3%; n=2). This age profile situates the sample within a generation of digital natives, who, generally speaking, should have had widespread access to digital devices, online platforms and algorithmic systems (CEDEFOP, 2021; Prensky, 2001). This pattern is consistent with the UTAUT model that identifies age and experience as key moderators of technology acceptance, In particular, younger users with high digital familiarity tend to report higher Effort Expectancy and are less dependent on Social Influence for technology adoption, as digital tools are already part of their everyday practices (Venkatesh et al., 2003; Venkatesh, Thong & Xu, 2012).

A crucial demographic-functional variable was self-perceived digital competence. The vast majority of students reported medium to high confidence in using new digital technologies: 32% (n=48) of the students declared themselves "very confi-

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dent" and 60,67% (n=91) "quite confident," whereas only 7,33% (n=11) reported low confidence. These findings further support the notion that the sample reflects the typical profile of digital natives, characterized by high familiarity and confidence in the use of digital technologies. Thus, approximately 92% of the sample exhibited medium-to-high digital autonomy. This finding is theoretically important because it implies that Effort Expectancy is unlikely to act as a barrier to AI adoption; instead, students' engagement with generative AI is driven primarily by whether the technology is perceived as useful and meaningful for learning (Performance Expectancy). The technological ecosystem in which these students operate further supports this interpretation. They report frequent use of smartphones, laptops, productivity software (Google Workspace and Microsoft Office), institutional learning platforms (Teams, Classroom, Drive), search engines (Google, Wikipedia) and generative AI tools such as ChatGPT in daily learning practices. This environment corresponds to high Facilitating Conditions within the UTAUT model because the students have continuous access to devices, connectivity and digital infrastructures that may make AI use both feasible and convenient.

2.5. Data analysis

Data analysis was conducted in three main steps using Jamovi. First, descriptive statistics (means, standard deviations) were calculated for each UTAUT construct to describe students' perceptions of generative AI. This step provided a general profile of acceptance, perceived usefulness, ease of use, social influence and motivational orientation. Secondly, scale reliability was assessed through Cronbach's alpha coefficients to verify the internal consistency of each construct. This procedure ensured that each composite score represented a coherent and stable measurement of the intended latent variable. Finally, to examine whether the seven UTAUT constructs were perceived differently by the same students, a repeated-measures Analysis of Variance (ANOVA) was used, with "Construct" (PE, EE, SI, FC, ATU, BI, IV) as the within-subject factor. This analysis is theoretically grounded in the UTAUT framework, which assumes that different determinants contribute in unequal ways to technology acceptance and behavioral intention (Adegbite, & Downe, 2013; Xue, 2024; Venkatesh et al., 2003; Williams et al., 2015). The assumption of sphericity was tested using Mauchly's test and, when violated, the Greenhouse–Geisser correction was applied to adjust degrees of freedom and obtain robust significance estimates. When the ANOVA revealed a significant main effect of the construct factor, post-hoc comparisons were carried out using Bonferroni and Holm corrections to identify which constructs differed significantly from each other. This step allowed a better interpretation of how students prioritize different dimensions of AI acceptance, such as usefulness, ease of use, affective attitude and intention to continue using the technology.

3. Results and discussion

The aforementioned analyses provided both a descriptive and inferential understanding of how generative AI is positioned within students' cognitive, motivational and behavioral frameworks, in line with the theoretical structure of the UTAUT model. Data shows that students primarily engage with AI when it enhances learning effectiveness, perceiving it as a form of cognitive support rather than a substitute for their own thinking. Moreover, acceptance of generative AI for academic purposes is moderate to high, with Performance Expectancy emerging as the strongest predictor of intention to use, confirming that perceived usefulness is the central driver of adoption. This effect is reinforced by high levels of Effort Expectancy and Facilitating Conditions, indicating that students not only find AI tools relatively easy to use but also perceive their digital environment as sufficiently supportive for effective integration. In contrast, Social Influence plays a limited role, suggesting that AI adoption is guided more by individual evaluation than by institutional or peer pressure. Relating to self-perceived digital autonomy and perceived stimulation in learning using digital technologies and AI, 92% reported that they had medium-to-high digital autonomy demonstrating that they feel very or quite confident in using new digital technologies (n = 48 very confident, n = 91 quite confident), indicating a population that approaches technological tools with competence and self-efficacy. Furthermore, students describe AI tools as stimulating and potentially useful, a perception that is reflected in elevated Attitude Toward Using (ATU) scores and reinforces their willingness to experiment with these technologies and to foster their learning with AI tools (e.g., Alexa, Google Lens, generative AI). While familiarity with specific AI tools varies, students consistently report interest and curiosity, positioning generative AI within an exploratory learning ecology rather than a mandated or routine practice.

Concerning descriptive analysis and scale reliability of UTUAT adapted version, for each construct, means and standard deviations were calculated to describe the level of each construct (PE, EE, SI, FC, ATU, BI, IV). Additionally, Cronbach's α was calculated to ensure that each construct reliably measured a consistent psychological dimension. Because all constructs were assessed within the same participants, a repeated-measures ANOVA was subsequently employed to determine whether students attributed the same weight to perceived usefulness, ease of use, attitude, facilitating conditions, and intention to use, or whether some dimensions were systematically more salient than others. In general, students demonstrated a moderately positive perception of the usefulness of AI for learning (Performance Expectancy, PE, M = 3.35, SD = 0.81), a good perceived ease of use of AI tools (Effort Expectancy, EE, M = 3.56, SD = 0.84), only moderate levels of perceived social influence from lecturers, peers, and the institution (Social Influence, SI, M = 3.17, SD = 0.69), and fairly adequate facilitating conditions supporting AI use (Facilitating Conditions, FC, M = 3.42, SD = 0.84). The Attitude Toward Using AI showed the highest mean value (ATU, M = 3.74, SD = 0.67), indicating a generally positive evaluation of AI as a learning support tool. Confidence and comfort when interacting with AI systems (Behavioral Intention, BI, M = 3.15, SD = 0.83) and the willingness to continue using or recommend AI tools (Intention to Use, IV, M = 3.46, SD = 0.86) were moderately positive.

All scales showed good internal reliability, with Cronbach's $\alpha \geq .73$. In particular, PE, EE, FC, BI and IV demonstrated very high reliability ($\alpha \geq .86$).

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Table 1. Descriptive Statistics and Reliability of the UTAUT Constructs

Construct	N	Mean	SD	Min	Max	Cronbach's α
Performance Expectancy (PE)	150	3.35	0.81	1.00	5.00	0.87
Effort Expectancy (EE)	150	3.56	0.84	1.00	5.00	0.87
Social Influence (SI)	150	3.17	0.69	1.33	5.00	0.74
Facilitating Conditions (FC)	150	3.42	0.84	1.00	5.00	0.86
Attitude Toward Using (ATU)	150	3.74	0.67	1.40	5.00	0.74
Behavioral Intention (BI)	150	3.15	0.83	1.00	5.00	0.88
IV – Intention to Use	150	3.46	0.86	1.33	5.00	0.87

The repeated-measures ANOVA revealed a highly significant main effect of construct, F (46.4, $p < .001$, with a large effect size ($\eta^2 p = .237$), indicating that students do not evaluate the different determinants of AI acceptance in the same way. Actually, perceived usefulness, ease of use, social influence, facilitating conditions, attitudes and intentions to use AI constitute distinct dimensions that contribute unequally to students' adoption of generative AI.

Table 2. Effects within subjects

	Sphericity correction	Sum of squares	gdl	Quadratical mean	F	p	η^2_p
Costructs	Greenhouse-Geisser	77.3	5.14	15.032	46.4	<.001	0.237
Residue	Greenhouse-Geisser	248.1	765.98	0.324			

Note. Sum of squares Type 3

The post hoc comparisons showed that Attitude Toward Using (ATU) was significantly higher than all other constructs, including Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Behavioral Intention, and Intrinsic Value (all $p < .001$). This finding highlights the central role of affective and evaluative components in shaping students' relationship with generative AI. Students do not merely perceive AI as useful or easy to use; rather, they develop a strongly positive emotional and cognitive attitude toward it as a learning support tool. This result is particularly relevant in educational contexts, where attitudes are known to influence sustained engagement and openness to pedagogical innovation (Ajzen, 1991; Scherer et al., 2019; Teo, 2011; Venkatesh et al., 2003). Performance Expectancy was also significantly higher than Effort Expectancy, Social Influence and Behavioral Intention confirming that perceived usefulness is a core driver of students' willingness to engage with AI. This aligns with the UTAUT model, which posits that Performance Expectancy is the strongest predictor of Behavioral Intention, especially in voluntary-use contexts. Students in this study appear to adopt generative AI primarily because it helps them learn more effectively, solve problems and support their cognitive processes, rather than because it is socially expected or institutionally promoted. Effort Expectancy is strong but not dominant. It was significantly higher than both Social Influence and Behavioral Intention, indicating that students generally find AI tools relatively easy to use, which lowers barriers to its experimentation and initial adoption. However, the absence of significant differences between Effort Expectancy and Facilitating Conditions suggests that ease of use is closely tied to the availability of technological resources and digital skills. This is consistent with the high levels of self-reported digital autonomy in the sample and with the presence of a rich digital ecosystem (smartphones, laptops, learning platforms, and AI tools), which together create favorable conditions for AI adoption.

In contrast, Social Influence consistently showed lower values and was significantly lower than the other constructs. It may indicate that students' intention to use AI is not socially driven because of peer pressure, teacher expectations or institutional norms, because they autonomously decide based on usefulness and interest. Finally, Behavioral Intention and Intrinsic Value (Intention to Use) seem to be the weakest construct It was lower than Attitude Toward Using and Performance Expectancy, and they also differed significantly from each other, with Behavioral Intention being lower than Intrinsic Value. This suggests that although students hold positive attitudes toward AI and recognize its value, their actual commitment to regular use is still developing. Generative AI appears to be in a phase of progressive integration into academic practices (Ciofalo, Pedroni, & Setiffi, 2024; Ranieri, 2024), more particularly, among the sample it is perceived as promising and engaging, but not yet fully embedded as a routine learning tool.

Table 3. Post Hoc Comparisons – Constructs

Comparison								
Constructs		**Constructs**	**Average difference**	**SE**	**gdl**	**t**	$p_{bonferroni}$	p_{holm}
PE	-	ATU	0.6613	0.0617	149	10.722	<.001	<.001
	-	EE	-0.2117	0.0584	149	-3.625	0.008	0.004
	-	SI	0.1756	0.0565	149	3.106	0.048	0.017
	-	FC	-0.0767	0.0603	149	-1.271	1.000	0.618
	-	BI	0.1967	0.0629	149	3.128	0.044	0.017
	-	IV	-0.1178	0.0477	149	-2.471	0.307	0.073
ATU	-	EE	-0.8730	0.0737	149	-11.849	<.001	<.001
	-	SI	-0.4858	0.0573	149	-8.479	<.001	<.001
	-	FC	-0.7380	0.0701	149	-10.533	<.001	<.001
	-	BI	-0.4647	0.0727	149	-6.392	<.001	<.001
	-	IV	-0.7791	0.0699	149	-11.147	<.001	<.001
EE	-	SI	0.3872	0.0592	149	6.539	<.001	<.001
	-	FC	0.1350	0.0518	149	2.604	0.213	0.061
	-	BI	0.4083	0.0626	149	6.519	<.001	<.001
	-	IV	0.0939	0.0581	149	1.617	1.000	0.432
SI	-	FC	-0.2522	0.0562	149	-4.490	<.001	<.001
	-	BI	0.0211	0.0586	149	0.360	1.000	0.949
	-	IV	-0.2933	0.0577	149	-5.083	<.001	<.001
FC	-	BI	0.2733	0.0612	149	4.464	<.001	<.001
	-	IV	-0.0411	0.0573	149	-0.717	1.000	0.949
BI	-	IV	-0.3144	0.0565	149	-5.561	<.001	<.001

Figure 1. Q–Q Plot of standardized residuals from the Repeated-Measures ANOVA.

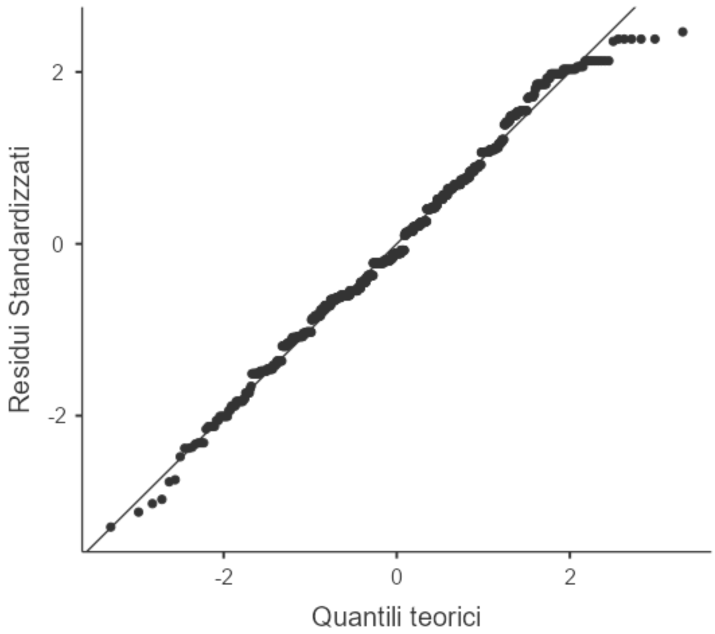

Table 4. Summary of significant and non-significant differences among UTAUT constructs

Construct	Holm – Significant	Holm – Not Significant	Bonferroni – Significant	Bonferroni – Not Significant
ATU	EE, IV, PE, FC, SI, BI	—	EE, IV, PE, FC, SI, BI	—
BI	EE, ATU, IV, FC, PE, SI	—	EE, ATU, IV, FC, PE	SI
EE	ATU, SI, BI, PE	FC, IV	ATU, SI, BI, PE	FC, IV
FC	ATU, SI, BI	EE, PE, IV	ATU, SI, BI	EE, PE, IV
IV	ATU, BI, SI	PE, EE, FC	ATU, BI, SI	PE, EE, FC
PE	ATU, EE, BI, SI	IV, FC	ATU, EE, BI, SI	IV, FC
SI	ATU, EE, IV, FC, PE, BI	—	ATU, EE, IV, FC, PE	BI

Results portray a student population that is cognitively, emotionally and technologically prepared to integrate generative AI into learning. Their adoption is primarily driven by perceived usefulness, ease of use and positive attitudes, whereas social pressures play only a marginal role. This configuration means that students are not resistant, that AI may be deeply integrated into learning, but a structured pedagogical grounding is necessary to transform attitude into routine use.

To conclude, from an educational perspective, this strong affective orientation toward AI resonates with the pedagogical tradition that conceptualizes technologies not as neutral tools, but as cultural mediators capable of reshaping cognitive, relational and professional practices. In particular, inclusive pedagogy emphasizes that learning technologies acquire educational value only when they are embedded within reflective, dialogic and ethically grounded practices (Bond et al. 2020; Di Domenico & Di Tore P. A., 2025; Dreytser, 2025; Sibilio, 2025; UNESCO, 2025). Within this framework, positive attitudes toward innovation are not merely individual dispositions, but significant conditions for the development of inclusive learning ecologies, where technologies function as supports for participation, personalization and critical engagement (Di Tore, P.A; Di Tore, S., Todino, n.d.; Lecce, Di Tore, 2025; Fiorucci, & Bevilacqua, 2024; OECD, 2025; Pagliara et al., 2024; Pinnelli, 2025; Salas-Pilco, Xiao, & Oshima, 2022). The prominence of Attitude Toward Using AI observed in this study may therefore be interpreted as an enabling factor for pedagogical innovation, if it is supported by professional guidance and reflective instructional design.

4. Conclusion

The findings of this exploratory study provide a nuanced picture of university students' acceptance of generative AI within higher education, highlighting the interplay between cognitive, affective, and contextual factors. Overall, students demonstrated moderate-to-high levels of acceptance, with Attitude Toward Using AI and Performance Expectancy emerging as the most salient dimensions. This suggests that generative AI is primarily perceived as a supportive learning resource that enhances academic effectiveness, rather than as a disruptive or externally imposed technology. Consistent with the UTAUT framework, perceived usefulness was a stronger driver of adoption than social influence, confirming that students' engagement with AI is guided mainly by individual evaluation and experiential benefits (Venkatesh et al., 2003). The limited role of Social Influence aligns with recent studies indicating that, in voluntary-use educational contexts, students rely more on personal judgment than on institutional norms when adopting emerging technologies (Khechine et al., 2020; Wong et al., 2023). Moreover, high levels of Effort Expectancy and Facilitating Conditions reflect a digitally mature learning environment in which technical barriers are minimal, allowing motivational and pedagogical factors to become central.

A particularly relevant result concerns the prominence of Attitude Toward Using AI. The strong affective orientation observed among students suggests openness, curiosity, and trust toward generative AI, which are critical conditions for sustained engagement and pedagogical innovation (Teo, 2019). However, the relatively lower scores for Behavioral Intention indicate that positive attitudes do not automatically translate into routine or systematic use. Generative AI appears to be situated in a transitional phase, recognized as valuable and engaging yet not fully embedded in academic practices. From an educational perspective, these findings underline the need for structured pedagogical frameworks that help students move from exploratory use toward reflective and responsible integration of AI. Without explicit guidance, there is a risk that AI remains an informal support tool rather than a resource aligned with learning objectives, critical thinking, and inclusivity (Holmes et al., 2022). This issue is particularly relevant for students in education-related degree programs, who will eventually shape how AI is introduced in school contexts. In this regard, the present study represents the first phase of a broader research trajectory. Future research will focus on iterative redesign and implementation of the RAG-based chatbot with future support teachers enrolled in the Specialization Course for Support Teaching at the University of Salerno. The next phase aims to align the tool more closely with authentic teaching workflows, particularly in the design of Individualized Educational Plans (IEPs) (Zappalà et al., 2025), while systematically exploring teachers' concerns, expectations, and ethical considerations. Through mixed methods, including surveys, focus groups, and interviews, the project seeks to deepen understanding of professional trust, pedagogical alignment, and inclusivity in AI-supported educational planning. Ample literature, including this research, highlights that generative AI holds significant potential as a dialogic and adaptive scaffold in higher and teacher education. However, policy makers and teacher educators need to bear in mind that its educational value depends heavily on how this technological sophistication is embedded within pedagogically sound, ethically grounded, and professionally meaningful practices. In summary, acceptance is a necessary but not sufficient condition: harmonizing heads, hands and hearts is essential for intentional instructional design and critical engagement (Pace & Zappalà, 2021) aimed at transforming positive attitudes into sustainable educational innovation.

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