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Future Teachers' Beliefs About Generative AI. Assessing Technology Acceptance as Students or as Aspiring Professionals

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Generative artificial intelligence (genAI) has undergone rapid advancements, presenting challenges to teacher education. In this study, we explore genAI acceptance among pre-service teachers, concerning both their roles as current students and aspiring professionals. Our survey engaged a sample size of 256 pre-service teachers drawn from six universities in French-speaking Switzerland. Their perspectives offer valuable context for understanding genAI acceptance and review the General Extended Technology Acceptance Model for E-Learning (GETAMEL), as genAI shows several peculiarities. For instance, the role of perceived ease of use has changed in predicting acceptance. As genAI continues to evolve, educators' viewpoints will significantly influence its adoption and transformation within educational contexts. Our results underscore the dynamic landscape of genAI in education and the importance of informed adoption strategies within teacher training institutions.

Keywords. generative artificial intelligence, teacher training, GETAMEL, technology acceptance, aspiring professionals

INTRODUCTION

Generative Artificial Intelligence (genAI) can be defined as the use of computer features with enormous processing capabilities that facilitate humanlike cognitive and functional abilities (Ouyang et al., 2022). Its rapid development led to the emergence of a set of easy-to-use tools presented today as solutions to produce a variety of media. Whether it consists of generating images (e.g., Dall-e 2), translations (e.g., Deep-L), texts (e.g., GPT-2), written interactions (e.g., ChatGPT), videos (e.g., Make-a-video), or multimodality (e.g., Gemini), these digital solutions based on large language models raise the question of how genAI will impact student work in academic contexts. Indeed, these contexts require not only learning, but also the production of documents which demonstrate learning, which could conflict with school or university practices.

Due to genAI's potential to increase productivity (Noy & Zhang, 2023), it has been "hyped" (Nemorin et al., 2023) to the point where it has been heralded as a turning point in teaching and learning. Some authors forecast the need to broaden the debate (van Dis et al., 2023), some see genAI as a threat to be managed (Brunadge et al., 2018), others envisage using it to understand human cognition (Goetschalckx et al., 2023), and some justify the need to reform the school system (Qu et al., 2022). Perceptions range from "melodramatically pessimistic" to "exaggeratedly optimistic" (Cave et al., 2023, p. 9), as genAI brings a number of seemingly attractive benefits, as well as risks that need to be addressed (Illich, 2021; Latour, 2010; Selwyn, 2016).

GenAI offers diverse prospects for education, from tools to simply access processed information, to those which individually support intellectual development (Yau et al., 2023) or promote teacher reflection on behavior management (Dann et al., 2021). The promised potentials for education and training transformations include the diversification of learning experiences, the personalization of instruction, greater interactivity, more formative assessments (Baidoo-Anu et al., 2023), or autonomy in education and development due to powerful intelligent tutoring systems (Qu et al., 2022). The narrative surrounding genAI also suggests that it could be the long-awaited solution for a child-centric education (Devi et al., 2022). However, working with the black box might not be obvious for teachers and learners (Bearman & Ajjawi, 2023).

At the tertiary level of education, the adoption of AI is variable, as some technologies seem to be widely accepted, while other more advanced techniques are less so (Ouyang et al., 2022). This can be attributed to the fact that, as with any technology, genAI requires a certain literacy (Holmes et al., 2022) and institutional constraints and latency are influential factors in its implementation (Okagbue et al., 2023). For students, the use of these generative technologies has been related to misconduct (Tindle et al., 2023), which could emphasize the need to guide learners toward ethical use. This seems especially important as it has been documented that university students do not have sufficient knowledge and experience with these tools (Kelly et al., 2023). These realities are leading universities to regulate usage with guidelines specifically focused on scientific integrity, evaluation design and communication with students (Moorhouse et al., 2023), as banning these technologies seems counterintuitive, both from an educational point of view and in terms of monitoring effective use. For instance, constructivist lecturing, collaborative team teaching, and peer assessment can be promoted as a means of designing a pedagogy aligned with technology (Quirke-Bolt, 2024).

Since genAI technologies are still in the early stages of application in education, especially for K-12 education (Tedre et al., 2021), literature provided is often theoretical and concerned primarily with the potential benefits and threat of AI, as well as a focus on guidelines (Popenici & Kerr, 2017). It is currently difficult to make clear recommendations for curriculum adaptations, beyond the usual suggestion for every new technology, where learners are invited to test the tools and to maintain a critical approach with them. The "how to" literature is certainly flourishing (Bearman & Ajjawi, 2023; Henriksen et al., 2023), but as genAI is claimed to have the capacity to revolutionize teaching praxis (Baidoo-Anu & Owusu Ansah, 2023), it seems important to document the perceptions and projected practices, with the aim of providing a clarified vision of the contribution of these tools to education and training.

If various AI systems have already been relatively well studied in terms of their applications in education and training (Holmes & Tuomi, 2022; Ouyang & Jiao, 2021)—differentiating (i) student-focused AI, (ii) teacher-focused AI, and (iii) institution-focused AI, for instance—, the generative variants of these technologies are much more recent. A scientific consensus seems to be lacking in genAI contribution for education and training.

Generative Artificial Intelligence in Teacher Education

In a recent literature review, the conclusion proposes that an effective use of genAI is possible in education (Zirar, 2023). For each customer, be they students or teachers, a systematic, critical evaluation of the outputs is necessary, focusing on their validity, reliability, and accuracy. The recommendation proposes a limited use of genAI for teachers when developing teaching and assessment materials, emphasizing the importance of clearly defining its role before delegating tasks to the technology. Pedagogical beliefs seem to affect the inclination to use genAI in the classroom (Choi et al., 2023), where constructivist beliefs enable these technologies to be accepted more readily. Additionally, it seems important to develop prompt engineering skills which are associated with content knowledge, critical thinking, and iterative design to empower students (Cain, 2024). Furthermore, it is important for teachers to prioritize unplugged activities for AI education (Jeon et al., 2020) and to demonstrate adequate data literacy skills (Dagienė et al., 2023).

Building upon Wiener's observation (1960) which noted that the complexity of a technology inversely affects our comprehension, the ethical considerations surrounding genAI usage in education now benefit from an expanding body of literature. Following a recent systematic literature review (Mouta et al., 2023), a wide diversity of ethical subdomains could be identified, including teachers' skills in exercising ethical judgment, overreliance on behaviorist and cognitive approaches that could sideline aesthetics or morality growth, or students' diversity and sense of agency in AI-based education. Fairness, non-maleficence, responsibility, pedagogical appropriateness, or freedom and autonomy are part of a long list of topics that need to be discussed before genAI can be deployed widely in education and training (Adams et al., 2023). This raises the question about the rationales driving what is considered adequate for genAI use in compulsory education and beyond.

In a theoretical perspective, a Human-AI Shared Regulation in Learning (HASRL) has been proposed as a continuation of socially shared regulation, where the HASRL model provides suggestions for future human-AI collaboration in learning and teaching (Järvelä et al., 2023). However, empirical data suggest that there is a risk of delegating the regulation of learning activities to AI because the technology is perceived as more effective than self-regulation strategies (Darvishi et al., 2024). This augmented perspective offers a counterbalance to an opposing viewpoint, wherein teachers consider genAI as a potential threat, fearing replacement of their role (Tao et al., 2019), within the framework of socially shared regulation of student learning. Human-machine interaction for learning regulation currently requires further active investigation to understand how genAI technologies must be promoted or regulated within different educational levels.

What emerges is that genAI in education are technologies that bring about a variety of perceptions, depending on whether they support existing processes, replace them, or constrain pedagogy. Research may not be sufficiently focused on how genAI could effectively be used by teachers (Salas-Pilco et al., 2022), and that there is only scarce literature documenting actual use, especially in the parameters of the present study (i.e., primary and secondary teacher education in French-speaking Switzerland). Consequently, the research questions raised pertain to the perceptions and projected uses of genAI among future primary and secondary teachers, as well as their willingness to integrate these technologies into their daily practices. Questioning the role of genAI in teacher education is increasingly vital, as it engages not only with students, but also with future teachers who may advocate for specific applications of genAI in the daily lives of pupils and young learners.

GenAI and Technology Acceptance

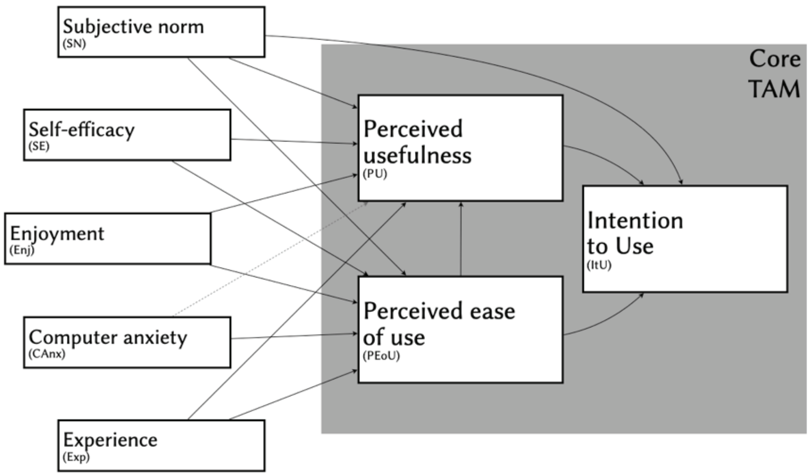
Several researchers have conducted studies to explain how a new technology is adopted and to identify the factors explaining its acceptance. Among these models, Davis (1989) developed the renowned Technology Acceptance Model (TAM). The TAM suggests that the acceptance of a new technology is indirectly determined by two variables: *perceived usefulness* (PU) and *perceived ease of use* (PEoU). According to the model, these two variables have a direct impact on *attitude*, which then influences the *intention to use* (ItU), ultimately reflecting in the *actual use*. PU is defined in the model as the degree to which an individual believes that using a particular technology would enhance their job performance. PEoU, on the other hand, refers to the degree to which an individual believes that using a particular technology would be effortless. The TAM quickly became a reference model to discuss technology acceptance, but it has also faced criticisms. For instance, it has been noted that the TAM defines usage intention as influenced by two factors, which in turn depend on external factors. However, the model does not provide any further information about these external factors. For this reason, numerous studies based on the TAM have attempted to investigate the external factors that could impact these two variables and consequently affect technology acceptance (Abdullah & Ward, 2016; Atarodi et al., 2019; Fathema et al., 2015; Fathema & Sutton, 2013; Park, 2009; Park et al., 2012; Scherer et al., 2019; Venkatesh & Davis, 2000).

Abdullah and Ward (2016) developed an extended model, called GETAMEL, based on a meta-analysis of 107 papers to identify the most commonly used external factors of TAM: *self-efficacy* (SE), *subjective norm* (SubNo), *enjoyment* (Enj), *computer anxiety* (CAnx), and *experience* (Exp). All these factors can predict PU and PEoU, except for CAnx, whose influence on PU was excluded from the proposed model. Additionally, SubNo can also directly predict ItU. Figure 1 illustrates the GETAMEL model and the way the various factors are expected to influence PU, PEoU or ItU.

Self-efficacy (SE) corresponds to the belief in one's ability to succeed in specific situations or accomplish a task (Bandura, 1978). SE affects an individual's motivation and their ability to exert effort to complete the task (Schunk, 1990) and can also influence the perception of the task at hand (Fathema et al., 2015; Fathema & Sutton, 2013; Park et al., 2012). Research shows that SE also predicts PU (Antonietti et al., 2022; Fathema et al., 2015; Ong et al., 2004; Ong & Lai, 2006), which also confirms an effect of efficacy on PEoU and ItU. In the technical context, SE is also associated with the belief of being able to successfully solve a task using a technology (Abdullah & Ward, 2016).

Figure 1

GETAMEL Model (Abdullah & Ward, 2016)



Subjective norm (SubNo) is defined as the expectation felt by the individual from various social groups (family, peers, colleagues, etc.) to adopt a certain type of behavior (Venkatesh et al., 2003). This factor has been included in the revision of the TAM by Venkatesh & Davis (2000) and further studies confirmed its importance in technology acceptance (Ursavaş et al., 2019). The reason for this resides in the fact that if a person perceives a drive to use a technology from its environment, they will incorporate this into their belief system and perceive the technology as more useful (Cheng, 2011).

Enjoyment (Enj) is defined in the context of technology acceptance as the extent to which the use of a specific tool is perceived as enjoyable, regardless of the performance consequences associated to it (Park et al., 2012). Previous research showed that Enj is linked with PEoU, PU, and ItU (Zare & Yazdanparast, 2013).

Computer anxiety (CAnx) is defined as a form of anxiety that is triggered when using technology and is associated with avoidance mechanisms or limitation in the use of tools and systems (Chen & Tseng, 2012). The relationship between CAnx and PU and PEoU is not necessarily significant. For instance, Abdullah and Ward (2016) found that while CAnx has a significant negative impact on users' PEoU in the context of e-learning (Abdullah

& Ward, 2016), it does not affect the PEoU of e-portfolios (Abdullah et al., 2016). Moreover, based on a review of seven studies, Abdullah and Ward (2016) concluded that there is no significant relationship between CAnx and PU in e-learning contexts. Consequently, this relationship was excluded from the GETAMEL model and was not examined in the context of e-portfolios (Abdullah et al., 2016).

Experience (Exp) in this context refers to computer-related experience, and it has been shown that individuals with extensive computer-related experience tend to have more positive PEoU and PU (Abdullah & Ward, 2016; Lee et al., 2013).

If TAM has been extensively adopted to understand teachers' acceptance of technology (Wijnen et al., 2023), only a limited number of studies have used it to analyze the acceptance of genAI. For instance, it has been proposed that ItU would still predict effective use, but personal innovativeness, habits, hedonic motivation, facilitating conditions, social influence, effort expectancy, and performance expectancy would predict ItU (Strzelecki, 2023).

Studies have been conducted which examine the beliefs and perceived trust of educational AI tools (Choi et al., 2023). PU and PEoU seem to be key factors in the acceptance of these technologies, at least in South Korea where the study was conducted. In Spain (Galindo-Domínguez et al., 2023), a generally positive attitude of K–12 teachers was documented, where content creation was the main purpose of genAI.

Technology Acceptance and Gender

Gender was not originally included in the TAM. However, in the adoption of a new software system, men's technology use was more influenced by PU compared to women's (Venkatesh & Morris, 2000), and the effects of PEoU and SN were more salient for women, but the effect of SN diminished over time. In a longitudinal investigation, the SN did not significantly influence men's decision to adopt and use a technology, and that attitude toward using it was more salient for men (Venkatesh et al., 2000). However, gender appears to work mostly in concert with age to moderate the effect of PU and of PEoU on the ItU (Venkatesh et al., 2003): PU was more significant for men and younger workers, whereas PEoU was more significant for women, particularly those who were older and with little experience with the technology.

In a recent study, Strzelecki & ElArabawy (2024) used the UTAUT framework (Venkatesh, 2022; Venkatesh et al., 2003)—another TAM variation—to investigate the moderating impact of two supplementary variables, gender and study level, on the acceptance and use of genAI (chatGPT) by Polish and Egyptian students. Study level replaced age in the UTAUT model. Gender appears to have had a significant influence in the Egyptian sample by moderating the path between PEoU and *behavioral intention* and the path between *social influence* and *behavioral intention* but had no effect in the Polish sample. In contrast, in both countries, the study level significantly moderated the relationship between *Social influence* and *Behavioral intention*. Among Egyptian students, the path between *Effort expectancy* and *Behavioral intention* was also moderated by the level of study. These results and the conceptual proximity between TAM, UTAUT and GETAMEL demonstrate an argument for the consideration of gender into the acceptance of technology. In addition, the GETAMEL model (Abdullah & Ward, 2016) does not explicitly observe the *actual use* and how this element relates with the ItU and other factors.

Research Questions

The aim of this research is to empirically document how future teachers in French-speaking Switzerland view the acceptance of genAI, as a current student in university education, and as a future professional in classrooms. More specifically, two research questions are addressed:

1. *How do GETAMEL factors affect future teachers' technology acceptance of genAI, in their roles as a student and as a future teacher?*
2. *How is the acceptance of genAI influenced by the gender and study level of future teachers?*

METHOD

Participants

The study employed an online survey to collect data. It was distributed per email in spring 2023 to ~3500 students enrolled in various teacher training programs (primary, secondary, and post-compulsory education) across six universities from French-speaking Switzerland, namely the University of Geneva, the University of Fribourg, and the Hautes Écoles pédagogiques of BEJUNE, Fribourg, Valais, Vaud. There were 256 fully completed questionnaires (~6.6% response rate). Female respondents comprised 198 individuals (77.3%), males accounted for 55 respondents (21.5%) and 3 respondents did not identify within these categories (1.2%), which roughly correspond to the current population in the teacher training programs targeted (70% of women), bachelor's or master's degrees. Ages ranged from 19 to 58 (*M*=28.47, *SD*=8.51).

Instrument

The data collection tool was based on a GETAMEL questionnaire version developed and tested in a similar context (Sprenger & Schwaninger, 2023). The technology focused on was identified as "genAI", and students were provided with the following definition at the beginning of the survey:

> *Computer processes that imitate human intelligence, built to generate content. The aim of these processes is therefore to enable machines to produce texts, images, music, videos, or other multimedia documents, perceived as plausible. Current examples include ChatGPT, Stable diffusion, Dall-e 2, and others.*

The French translation of the questionnaire was discussed and analyzed by five researchers to guarantee understanding of items, and suitability with genAI technologies. The measurement scale of the GETAMEL being used included a total of 26 items, of which 15 items for all five external factors were added to the model, 4 items respectively for PEoU and PU, and 3 items to evaluate ItU. Each item was measured on a Likert scale of 1 to 7 (1 = totally disagree and 7 = totally agree). The link between CAnx and PU was explored in our study even if it was excluded from GETAMEL in the context of e-learning adoption (Abdullah & Ward, 2016). The questions associated with PEoU, CAnx, Enj, Exp and SubNo were asked without segmentation of the roles (students *vs.* future teachers). However, questions associated with self-efficacy (SE*teac* / SE*stud*), perceived usefulness (PU*teac* / PUstud), and intention to use (ItU*teac* / ItU*stud*) were asked twice, once to be answered as current students, once to be answered as future teachers. The study also included questions to inquire about study level and gender. Study level was assessed using two options: bachelor's and master's degrees. The three-year bachelor's degree in Primary Education included three items for each year of the training (e.g., B1, B2, B3) whereas the two-year master's degree in Secondary School Teaching as well as other specialized master's in education was composed of two items (e.g., MASE1, MASE2). The "gender" dimension has been approached by three options: female, male and "does not assign oneself to one of these two categories."

In addition to these items, other questions were added to document knowledge, experience, the potential uses of genAI as students and teachers, current relations to self-regulated learning and projections of genAI for the future of education. But these data will not be addressed within the scope of this article.

Students were free to respond to the questionnaire, which was sent by email, inviting them to anonymously give 25 minutes of their time on-line, to understand the uses of generative AI by students in teaching. The data was stored in a password-protected institutional drive (SWITCHdrive) shared between the co-authors only.

RESULTS

Describing the Data

This section presents a description of the data pertaining to the different GETAMEL factors (see Table 1). For most of the factors related to genAI acceptance, pre-service teacher***s*** tend to disagree about the items associated with these variables (average score below 4). When asked to adopt a future teacher's perspective, pre-service teachers seem even more uncertain about the PU of genAI, about their SE and ItU. The differences of averages between the two perspectives (teachers/students) are significant for these factors (PU = $t(255) = 4.92$, $p > .001$; SE = $t(255) = 3.41$, $p > .001$; ItU = $t(255) = 5.56$, $p > .001$). In contrast, PEoU was considered quite important by respondents (M= 4.7; SD = 1.53) and reported Enj had no clear-cut orientation (M = 4.01; SD = 1.54). The relatively high standard deviations for all the factors, from 1.47 to 1.92, indicate a wide range of perceptions about genAI, especially for ItU when adopting a student perspective (M = 3.94; SD = 1,921).

Table 1

Descriptive Statistics and Normality Tests

Variables	Described as a…	Mean	Std. Dev.	Skewness	Kurtosis	Range
PEoU	User	4.743	1.527	-.559	-.366	6
CAnx	User	3.492	1.684	.330	-.871	6
Enj	User	4.087	1.548	-.042	-.648	6
Exp	User	3.254	1.531	.440	-.590	6
SubNo	User	3.181	1.473	.483	-.523	6
SE	Student	3.932	1.645	-.057	-.790	6
	Teacher	2.667	1.553	.126	-.596	6
PU	Student	3.935	1.721	-.054	-.861	6
	Teacher	3.497	1.701	.333	-.800	6
ItU	Student	3.940	1.921	.067	-1.186	6
	Teacher	3.465	1.739	.291	-.841	6

Future Teachers' Technology Acceptance of genAI

To evaluate the adherence of our data to the GETAMEL model, two structural equation models were performed. Data were organized to create one model concerning the representation and ItU as students, while the other was focusing on the projection and ItU as future teachers. Structural equation model (SEM) analyses were performed with *R lavaan*, 0.6.15 version (Rosseel, 2012), to determine the presence of relations between observed variables, knowing that the GETAMEL model used in the context of this research comprises 8 variables (Exp, SubNor, Enj, CAnx, SE, PU, PEoU, and ItU).

SEM for data reported as students concerns 256 observations. The results of the model in terms of adherence to the data are the following: $\chi 2(11) = 195.03$, $p <.0001$; Comparative Fix Index = 0.820; Tucker-Lewis Index = 0.575; Root Mean Square Error of Approximation = 0.256 [0.225; 0.288]; Standardized Root Mean Square Residual = 0.094. The coefficients of the path analysis that reach the conventional threshold for statistically significant alpha < .05 are reported in Figure 2 and Table 2.

Figure 2

SEM Performed on Data Reported as Students

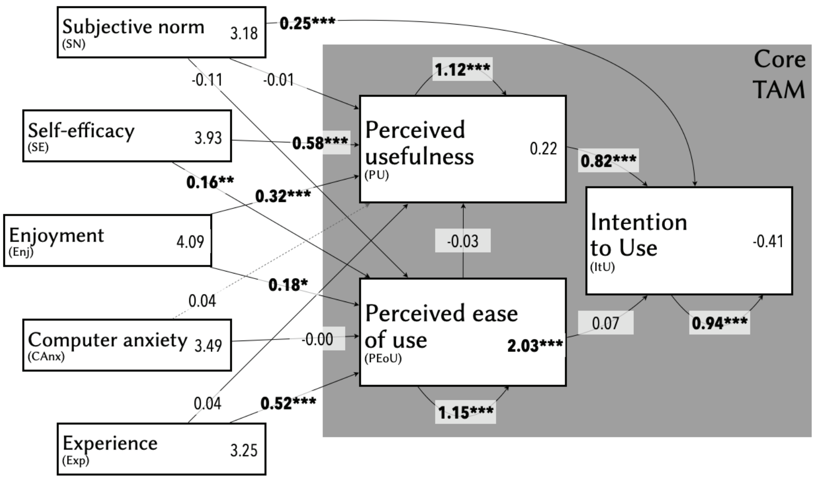


Table 2

Parameter Estimates for Data Reported as Students (Significant Results Only)

Regression	Estimates	Standard error	*z*-value	*p*
SE —> PU	0.585	0.06	9.825	<0.001
SE —> PEoU	0.161	0.057	2.814	0.005
Enj —> PU	0.319	0.076	4.221	<0.001
Enj —> PEoU	0.184	0.073	2.526	0.012
SN —> ItU	0.247	0.047	5.288	<0.001
Exp —> PEoU	0.517	0.056	9.152	<0.001
PU —> ItU	0.819	0.042	19.573	<0.001

SEM for data reported as future teachers concerns 256 observations. The results of the model in terms of adherence to the data are the following: $\chi 2(11) = 210.47$, $p < .0001$; Comparative Fix Index (CFI) = 0.801; Tucker-Lewis Index (TLI) = 0.529; Root Mean Square Error of Approximation (RMSEA) = 0.266 [0.235; 0.298]; Standardized Root Mean Square Residual (SRMR) = 0.112. The coefficients of the path analysis that reach the conventional threshold for statistically significant alpha < .05 are reported in Figure 3 and Table 3.

Figure 3

SEM Performed on Data reported as Future Teachers

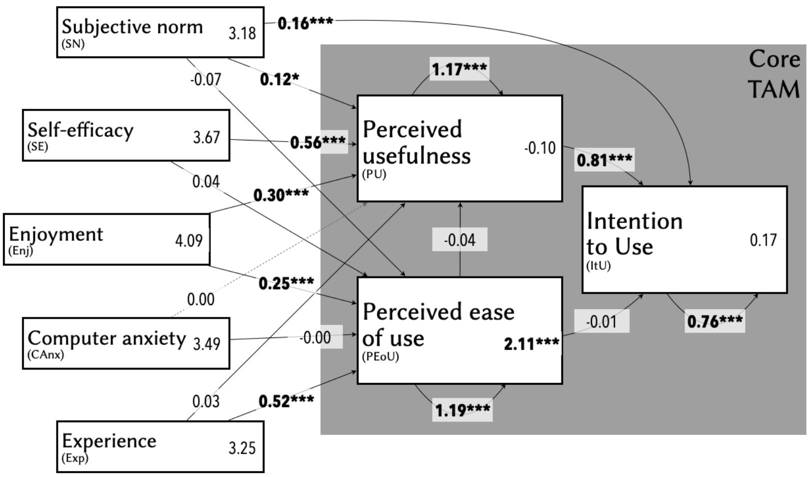


Table 3

Parameter Estimates for Data Reported as Future Teachers (Significant Results Only)

Regression	Estimates	Standard error	*z*-value	*p*
Exp —> PEoU	0.523	0.057	9.132	<0.001
SubNo —> PU	0.115	0.057	2.017	0.044
SubNo —> ItU	0.157	0.043	3.637	<0.001
Enj —> PU	0.298	0.073	4.093	<0.001
Enj —> PEoU	0.254	0.072	3.543	<0.001
SE —> PU	0.563	0.056	10.063	<0.001
PU —> ItU	0.815	0.038	21.322	<0.001

We evaluated the fit of SEM based on the common guidelines for an acceptable model fit (CFI ≥ 0.95, RMSEA ≤ 0.08, and SRMR ≤ 0.10). These comparative thresholds were adopted from Scherer et al. (2019, p. 21). With these thresholds, both models (students and future teachers) provide a poor fit at a global level. At the local level, there is a better fit, with the statistically significant paths that are highlighted in Figures 2 and 3.

Gender and Study-Level Differences in genAI Acceptance

Women constitute 78% of our sample (*N*=198), a proportion closely aligned with representation in the broader population of prospective teachers across the six teacher education institutions included in our investigation. To explore the dissimilarities between these two groups, we employed the non-parametric Mann-Whitney U test due to the disproportion in sample size between female and male participants. The results indicate that there are important gender differences between all factors related to genAI acceptance, as detailed in Table 4. Specifically, the gender disparities are pronounced for Enj and Exp with genAI, with a $p < .001$. For SubNo, the difference is less evident, but still noteworthy.

Table 4

Gender Differences in the Dataset According to GETAMEL Model

		Female (N= 198)		*Male (N = 55)*		*Mann-Whitney*		
Variables	As a...	*M*	*SD*	*M*	*SD*	*U*	*z*	*p*
PEoU	User	4.62	1.55	5.14	1.38	4,332,000	-2.324	.020
CAnx	User	3.66	1.69	2.90	1.55	4,009,500	-2.996	.003
Enj	User	3.83	1.53	4.92	1.26	3,244,000	-4.602	<.001
Exp	User	2.99	1.45	4.15	1.46	3,096,500	-4.903	<.001
SubNo	User	3.07	1.47	3.48	1.43	4,516,500	-1.940	.052
SE	Stud	3.76	1.67	4.45	1.38	4,046,500	-2.919	.004
	Teac	3.51	1.55	4.13	1.43	4,125,000	-2.757	.006
PU	Stud	3.79	1.74	4.36	1.57	4,385,500	-2.210	.027
	Teac	3.31	1.65	4.06	1.74	4,126,500	-2.750	.006
ItU	Stud	3.72	1.93	4.59	1.73	4,021,500	-2.976	.003
	Teac	3.28	1.70	4.06	1.72	4,112,500	-2.784	.005

In our investigation about the study level, we employed the Kruskal-Wallis Test due to the non-normal distribution of most of our variables. The outcomes indicate that across all GETAMEL factors, there is no discernible distinction between students enrolled in bachelor's programs and those in master's programs, irrespective of their academic year. However, an exception arises for the PU factor, where students' responses exhibit a tendency to diverge ($H(4) = 9.17$, $p = .057$) based on their study level (bachelor's or master's degrees), as perceived from a student's standpoint. Notably, subsequent post hoc comparisons, adjusted using the Bonferroni correction, reveal no statistically significant differences among the various pairs of groups.

DISCUSSION

The above-mentioned results make it possible to answer our two research questions.

GenAI Acceptance by Students and Future Teachers

The data collected show a certain adherence to the GETAMEL theoretical model, even though not all factors interact as expected. As far as PU is concerned, this factor was examined across the two distinct datasets. The first focused on (i) students' perspectives, while the second considered (ii) future teachers' viewpoints. In line with our reference model (Antonietti et al., 2022; Fathema & Sutton, 2013), we found that PU was well predicted by SE and Enj in both datasets. However, the influence of SubNo on PU exhibited variability between the two datasets. With future teachers' perspective (ii), the data aligns with the GETAMEL, as PU is indeed predicted by SubNo albeit with a limited impact. With students' representations (i), SubNo does not play a significant role in predicting PU. These results suggest that the PU of genAI tools might not be strongly associated with SubNo. Interestingly, regardless of the perspective adopted, SubNo directly impacts ItU, emphasizing its plausible relevance in the context of genAI tools in education and training. The narrative surrounding the thoughtful and critical integration of digital technology in education and training has been around for a long time. This is undoubtedly linked to the need for guidance on how to work with a black box (Bearman & Ajjawi, 2023) and the role of policymakers (Okagbue et al., 2023) and teacher training institutions regulating genAI use when the data have been collected.

Remarkably, for both datasets, we did not discern the influence of one factor that should theoretically predict PU according to the GETAMEL (Abdullah & Ward, 2016): Exp. One plausible explanation is that this technology was relatively nascent at the time of data collection, which might partially account for the divergent role of experience in predicting the utility associated with these tools compared to its typical impact with more conventional tools. In accordance with Abdullah & Ward findings (2016), there is a lack of significant relationship between CAnx and PU. It can be argued that GenAI tools are exceptionally intuitive and do not necessitate advanced computer proficiency. Once again, the recent popularity of this technology may well have obscured associated sources of anxiety, such as data protection or the performance implicit in it. Furthermore, the usage projections collected were overwhelmingly focused on learner use. CAnx would probably be different if the projections called for were oriented toward teacher use, for continuing education or teacher reflection for instance (Dann et al., 2021), toward perceived implications for pedagogy (Quirke-Bolt, 2024), or toward HASRL where teachers may lose a part of their ability to affect learners' experiences (Järvelä et al., 2023).

As anticipated (Lee et al., 2013), our data reveals a robust association between PEoU and Exp. The inherent simplicity of popular genAI interfaces appears to significantly influence how users perceive them as user-friendly, particularly when they have experience with these tools. Additional GETAMEL factors that can predict PEoU are Enj and SE. As far as, Enj in concerned, the effect of this factor is observed in our datasets, even though it is weak. SE, on the other hand, shows a different effect in our two datasets: when measured from students' viewpoints (i), SE emerges as a strong predictor of PEoU. Notably, it impacts both PU and PEoU. In contrast, SE does not significantly predict PEoU when adopting the perspective of future teachers (ii). Instead, its impact is primarily confined to the former factor, PU.

Contrary to expectations based on GETAMEL developed for e-learning (Abdullah & Ward, 2016), neither CAnx nor SubNo exhibit any discernible influence on PEoU. However, our findings align with the lack of a significant link observed between CAnx and e-portfolios (Abdullah et al., 2016). We can conclude that CAnx stands out as the sole factor for which we failed to discern any impact on the acceptance of genAI. Intriguingly, this factor does not appear to predict either PU or PEoU. This observation could be attributed to the nature of genAI tools, which do not necessitate advanced computer skills, as previously mentioned. The PEoU doesn't seem to be directly linked to understanding the tool, a far more significant issue (Bearman & Ajjawi, 2023). In addition to this interpretation of the lack of CAnx influence, the topical issue at the time of data collection was what kind of pedagogy could be envisaged with genAIs (Tedre et al., 2021). The user interface, which emphasizes text-based prompts, may be tailored specifically to bachelor's and master's students, who are accustomed to reading and writing, but its usefulness was still up for discussion.

In both datasets we clearly observe that PU strongly predicts ItU for this technology, aligning with the GETAMEL. Furthermore, these findings underscore the critical importance of enhancing students' and future teachers' comprehension regarding the potential of genAI. Consistent with the GETAMEL, SubNo directly influence ItU in both of our datasets. To foster the adoption of genAI among students and future teachers, university authorities might consider encouraging those university teachers and fellow students who already utilize genAI responsibly to promote its adoption.

One of the most intriguing findings lies in the fact that ItU does not appear to be influenced by PEoU in either of our datasets. This divergence from the anticipated relationship posited by the GETAMEL and other variants of the TAM warrants exploration. This result calls into question the literacy needed to use genAI (Holmes et al., 2022) or the prompt engineering skills (Cain, 2024), at least in the perceptions of those surveyed. Several hypotheses can be formulated to elucidate this phenomenon. One plausible explanation is that the inherent practical simplicity of genAI tools effectively removes PEoU as a decisive factor in determining users' intentions to adopt this technology. In essence, the straightforwardness of genAI tools may render the evaluation of their usability less critical when individuals contemplate their adoption. Another plausible explanation is that other factors, like pedagogical beliefs (Choi et al., 2023), play a far more important role and thus reduce concerns about ease of use.

As far as the model fit is concerned, the model is only partially fit to the data at the local level, with some relations within variables showing high residuals in the covariance, which negatively impact the global fit. Considering that the TAM has been shown to provide a good fit for technology acceptance (Scherer et al., 2019) and that data are based only on a limited number of survey items, it is conceivable that misfits are due to the way the dimensions were implemented through the items rather than a distinct acceptance of AI.

GenAI Acceptance, According to Gender and Study Level

The study reveals a significant influence of gender on genAI acceptance. If social and cultural factors have been studied extensively to account for these differences, recent meta-analyses (Borokhovski et al., 2018; Cai et al., 2017) demonstrate that certain differences—such as SE toward technology and motivation—have diminished over the past two decades. Interestingly, while attitude toward technologies remains more pronounced among men, it is noteworthy that genAI acceptance remains largely unaffected by the academic year of study or the students' experiences with AI-generated content throughout their teacher training institute curriculum. This observation underscores the nascent stage of genAI within the education sciences academic community.

In summary, gender seems to play an important role in shaping perceptions of genAI, but other factors, including SE and motivation, also contribute to the evolving landscape of AI acceptance in educational contexts. As genAI continues to develop, understanding these dynamics becomes essential for informed decision-making and effective integration into educational practices.

GenAI Acceptance in Teacher Education, Within Limits

The findings of our study should be interpreted with caution due to several limitations. Given the study's contextual specificity and its methodological constraints, readers should interpret the results acknowledging these inherent limitations. First, the response rate in our study was relatively small. While it is challenging to ascertain, it is plausible that early adopters or individuals with strong opinions—either in favor of or against innovation—were more likely to participate. Consequently, potential biases may exist in the collected data. Second, we introduced gender and study level as additional factors, which were not part of the original GETAMEL framework. Although similar theoretical models (such as the UTAUT) account for these factors, their inclusion raises questions about the theoretical framework's coherence. The differences observed warrant further investigation into the interplay between these variables. Finally, it is essential to recognize that our surveyed population consisted exclusively of university students. As such, the nuanced roles of specific factors in the acceptance and utilization of genAI within educational contexts may not be generalized to other populations. Future research should explore these factors across diverse groups to enhance our understanding of genAI adoption. In summary, while our study sheds light on genAI use, these limitations underscore the need for cautious interpretation and encourage further exploration of the complex interrelationships among context, factors, and outcomes in the realm of educational technology.

CONCLUSION

In this study, we delved into the acceptance of genAI within the context of teacher training. Our investigation considered two distinct vantage points: that of current students and of aspiring teachers. The results illuminate subtle divergences in their attitudes and preparedness to adopt technological innovations. Indeed, prospective teachers exhibit a dual perspective when encountering genAI. Specifically, SubNo—shaped by social influences and peer expectations—that should play a distinct role in predicting PU, were weighted less influential as students. SE and Enj differentially impacted PEoU.

PEoU has an intriguing position in this context, because it does not significantly impact PU or ItU. This pattern warrants further exploration. Furthermore, CAnx did not directly affect PEoU. We posit that the unique characteristics of our surveyed population—university students preparing for teaching roles—and the specific genAI interface based on text prompting contribute to the observed PEoU factor without substantial influence on the TAM. We also documented differences according to genders, even though this factor is not included in the GETAMEL, where men showed a more pronounced positive attitude toward genAI. Our results reflect those of previous studies, where K-12 teachers showed simultaneously concerns about ChatGPT on learning and teaching and engage in the quest for constructive use of genAI in the classroom (Hays et al., 2024), between opportunities and challenges (Mao et al., 2024), as always with new technologies.

In summary, according to our results, the GETAMEL factors that affect future teachers' technology acceptance of genAI (research question 1) are subjective norm, self-efficacy, enjoyment, and perceived usefulness. Computer anxiety, experience, and perceives ease of use do not influence the intention to use genAI. If study level shows no impact on genAI acceptance, gender (research question 2) disparities are important for enjoyment, experience, and subjective norms, with males more inclined to genAI.

Our study underscores the multifaceted nature of genAI acceptance and emphasizes the need for tailored interventions and training programs. As the field evolves, continued research will refine our understanding and inform effective strategies to clarify genAI adoption among future educators.

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