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The impact of artificial intelligence on maker education: Motivation and technology acceptance in teacher training

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Abstract

In recent decades, the integration of emerging technologies, such as maker education and artificial intelligence, into the educational field has become a prominent area of research. The purpose of this article is to explore whether the introduction of generative artificial intelligence into the design process of maker projects by future teachers produces benefits. Specifically, a comparison was made between the perceptions of trainee teachers who experimented with the use of generative artificial intelligence and those who did not use it during the development of teaching and learning designs. A questionnaire was administered to a sample of 114 trainee teachers from the University of the Basque Country (UPV/EHU), who received training in maker education and designed teaching and learning plans based on this approach. The results of the comparison indicate a significant difference between the two groups across all analyzed dimensions, highlighting that the group working with artificial intelligence demonstrated greater motivation, particularly in terms of attention and acceptance of maker education. The findings suggest that the design process of future AI-based maker interventions should be explored more thoroughly in several dimensions related to the integration of emerging technologies.

Keywords: Artificial intelligence, curriculum development, educational technology, maker education, teacher education, teaching innovation.

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Contents

Contribution of this paper to the literature

The article examines whether integrating generative artificial intelligence into maker project design can enhance pre-service teachers' motivation and acceptance of technology in maker education. It compares perceptions between two groups those without AI experience and those with AI experience highlighting key differences in their attitudes and perceptions.

1. Introduction

Research into emerging technologies such as maker education in formal education appears to be increasing in both pre-service and in-service teaching. A significant number of studies have focused on training future teachers to develop competencies in the design and planning process in accordance with maker principles (Douglass & Verma, 2022; Heredia & Fisher, 2022; Shively, Hitchens, & Hitchens, 2021). Recent studies indicate that the incorporation of maker education into formal learning environments fosters and promotes skills related to science, technology, engineering, and mathematics (STEM) (Blackley, Sheffield, Maynard, Koul, & Walker, 2017). In this field, there is also an increasing emphasis on the integration of artificial intelligence (AI) because it holds significant potential to expand the range of study opportunities and practical experiences available to students (Wu, Lee, Wang, Lin, & Huang, 2023). The integration of AI, particularly generative artificial intelligence (GenAI), within the educational sector has given rise to a multitude of opinions and perspectives, primarily due to its potential to transform the educational landscape (Tlili et al., 2023). A considerable body of research has been published demonstrating the effectiveness of using GenAI as a pedagogical tool, highlighting how it can improve teaching and learning outcomes (Ali, Shamsan, Hezam, & Mohammed, 2023; Eager & Brunton, 2023). Both emerging technologies have been shown to have a significant impact on students' feelings and attitudes towards learning, resulting in increased enthusiasm for it (Ou & Chen, 2024). There are even studies that recommend introducing AI education courses into teacher training programs (Sun, Tian, Sun, Fan, & Yang, 2024). However, in the field of teacher training, there are still aspects to be explored, such as the perceptions of pre-service teachers.

This article advances research on how emerging technologies can be integrated into education. Its primary aim is to analyze the perceptions of early childhood and primary education trainee teachers regarding maker education, particularly concerning its impact on motivation and the acceptance of technology when other emerging technologies, such as artificial intelligence, are introduced. The study has two main objectives: first, to compare the perspectives of two groups of trainee teachers one working solely with maker education and the other integrating AI; second, to examine the role of GenAI tools in lesson planning, analyzing how the group using GenAI tools differed from the group designing their teaching and learning plans without AI support.

1.1. Maker Education in the Educational Field

The maker movement is a phenomenon that brings together diverse agents to form communities focused on tinkering, creating, and building unique artifacts (Peppler & Bender, 2013). Rooted in the do-it-yourself (DIY) mindset, its pedagogical foundations trace back to John Dewey's emphasis on active participation in learning (Martinez & Stager, 2013) and Seymour Papert's constructionism, which highlights the potential of creation over mere knowledge transmission (Halverson & Sheridan, 2014). The constructionist approach, which was derived from Piaget's constructivism, argues that learning occurs through the creation of tangible artifacts (Papert & Harel, 1991). The constructionism incorporates a number of pedagogical approaches such as project-based learning, inquiry-based learning, and collaborative learning (Schlegel et al., 2019). Makerspaces, as physical or virtual collaborative learning environments, serve as global and technological learning spaces equipped with tools and materials that support creativity, problem-solving, and knowledge sharing (Gantert, Fredrich, Bouncken, & Kraus, 2022). Those learning environments could be defined as creative and adaptable learning environments (Soomro, Casakin, Nanjappan, & Georgiev, 2023).

A substantial and progressive increase has been observed in the number of published manuscripts related to maker education in recent years and in relation to the educational field. This phenomenon reflects its growing popularity across all educational levels, from primary schools to higher education (Soomro et al., 2023). However, challenges exist, particularly for elementary teachers, who may struggle with the content, delivery methods, and physical spaces of makerspaces. This highlights the need for specialized teacher training to support these innovative learning environments (Douglass & Verma, 2022). A broad range of study participants has been explored, including in-service and pre-service teachers, as well as other agents involved in workshops and training courses (Heredia & Tan, 2021; Koole, Anderson, & Wilson, 2020). Programmes targeting future educators aim to address the challenges of incorporating maker activities into conventional classrooms by providing collaborative support and hands-on experiences, thereby fostering both theoretical understanding and practical expertise (Douglass & Verma, 2022; Heredia & Fisher, 2022). Other programs focus on effective professional development through immersive virtual environments that foster collaboration and community (Lock et al., 2020; Morrison & Hughes, 2023) or through on-site training, with a view to better integrating maker practices into curricula and addressing challenges such as content dread (Heredia & Tan, 2021).

1.2. Artificial Intelligence in the Educational Field

The use of artificial intelligence in everyday tools and its consequent redefinition of services in higher education have been well documented (Popenici & Kerr, 2017). The interest in the use of AI in educational settings has experienced notable growth in recent years (Celik, Dindar, Muukkonen, & Järvelä, 2022; Popenici & Kerr, 2017). Research studies have predicted a rise in the number of studies that will be carried out, with the application of AI to educational environments. There will also be an increase in the number of studies discussing possible approaches to promoting and teaching AI skills at all educational levels and in all fields (Hwang, Xie, Wah, & Gašević, 2020).

In the context of teacher training, positive perceptions have been identified regarding the use of GenAI in educational environments, indicating opportunities for its integration into teaching practices (Lozano & Blanco Fontao, 2023). It possesses the potential to reduce the workload of teachers, facilitating the efficient creation of course materials, although the teaching units may be somewhat generic and require further refinement (Cooper, 2023).

Moreover, research has demonstrated the benefits of GenAI in helping students identify sources of inspiration for composition and content evaluation tasks (Fergus, Botha, & Ostovar, 2023). Moreover, it has been observed that it has the capacity to facilitate the generation of ideas and to provide explanations that are acceptable in a variety of knowledge domains. This, in turn, has the effect of enhancing the accessibility, efficiency, and efficacy of academic counseling (Akiba & Fraboni, 2023). Within the domain of university students, this tool is not perceived as a threat to the education system, provided that the data generated is verifiable (Lozano & Blanco Fontao, 2023). However, GenAI also exhibits certain weaknesses that should be taken into account. It has been argued that it may not be suitable for novices, as its responses may lack logical coherence and require prior knowledge. In some cases, the information provided may not be entirely accurate, and in others, the responses may be contradictory, which may lead to questions regarding the reliability of the information provided (Stojanov, 2023). The didactic designs it creates can be generic and require adaptation by teachers (Cooper, 2023). There are studies that argue that the utilization of AI may have the potential to diminish critical thinking skills and that its efficacy can vary across different subjects (Mohamed, 2024). It is acknowledged by many teachers that the implementation of AI in the educational sector may be useful for reducing the time spent on administrative tasks and facilitating the creation of engaging and personalized learning experiences. However, there are concerns regarding the effort required to train teachers, the potential consequences for employment due to job displacement, the impact on creativity and critical thinking skills, as well as the dependency on AI's capacity to function without error (Alwaqdani, 2024). A recent study has indicated that reliance on AI tools alone may not be sufficient to enhance motivation when confronted with challenging programming tasks (Yilmaz & Yilmaz, 2023).

Consequently, there is a necessity to provide training and education to the education community, comprising teachers and students, in order to ensure the responsible and ethical use of generative artificial intelligence in educational practice (Zhu, Sun, Luo, Li, & Wang, 2023).

1.3. Artificial Intelligence and Maker Education

In recent years, there has been an increase in the popularity of education in artificial intelligence (Ng et al., 2023). Initiatives are being undertaken in the education sector to increase student literacy in AI and to cultivate collaborative problem-solving skills. Institutions are integrating the field of AI into STEM education and computer science curricula. The purpose of this integration is to cultivate AI literacy among students through an interdisciplinary approach. Additionally, the integration of AI into educational practice has been shown to inspire students to solve problems in STEAM subjects (Sintov et al., 2016). Authors place an emphasis on the fact that AI can be used to communicate and collaborate with colleagues (Carpio Cañada, Mateo Sanguino, Merelo Guervós, & Rivas Santos, 2015).

Few studies have explored maker education as a strategy for AI literacy. A recent study researched its integration at different cognitive levels, highlighting improvements in motivation, professional interest, confidence, and collaboration (Ng, Su, & Chu, 2024). It has also been determined that maker pedagogy has the potential to be an effective approach in providing students with opportunities to explore playful tools and materials for meaningful practical creation. The objective of this approach is to improve AI literacy through the implementation of a 'learning by doing' strategy (Hsu, Abelson, Lao, Tseng, & Lin, 2021).

In fostering greater confidence in AI and in relation to studies that have analyzed the degree of acceptance of this emerging technology, it is noteworthy that teachers' acceptance of educational AI tools is influenced by perceived usefulness, perceived ease of use, and perceived trust (Choi, Jang, & Kim, 2023). It should also be emphasized that it may be necessary for educators to be informed about the AI decision-making process and its potential to enhance and complement their skills rather than replace them (Nazaretsky, Ariely, Cukurova, & Alexandron, 2022). Another piece of research that analyzed the acceptance of AI concluded that, in a sample of 200 teachers, they had a positive attitude towards AI, finding a significant positive correlation between perceived usefulness, perceived ease of use, and a positive attitude towards AI (Herzallah & Makaldy, 2025).

In light of the growing interest in emerging technologies such as maker education and artificial intelligence, it is evident that previous studies have yet to analyze the perceptions of trainee teachers towards maker education in two different contexts: one without AI and the other with AI. The present study therefore poses the following research questions:

1.4. Research Questions

The following research questions are proposed.

RQ1. Do the two groups, the Non-AI and AI pre-service teachers, exhibit divergent perceptions of motivation towards maker education upon completing the project design?

RQ2. Do the two groups, Non-AI and AI, demonstrate differences in technology acceptance towards maker education upon completion of the project design? Which subcategories exhibit the most significant differences?

2. Method

2.1. Participants and Design of the Intervention

The present investigation was conducted with a sample of 114 trainee teachers enrolled in the Information and Communication Technologies (ICT) subject at the Faculty of Education of the University of the Basque Country. The participants were enrolled in bachelor's degree programs in Early Childhood Education and Primary Education during the 2022/23-24 academic year.

The 16-week course included a three-week segment focused on maker education, incorporating both theoretical and practical approaches. Theoretical classes provided an overview of the stages and principles of the maker education methodology, while practical sessions were conducted in a maker laboratory, a collaborative learning environment located at the Faculty of Education. Participants were tasked with designing teaching and learning plans that employed the maker pedagogical approach through project-based learning, integrating theoretical knowledge with practical experience. Participants had the opportunity to experiment with all the tools and materials available in the maker laboratory. The curriculum for initial teacher training programs emphasizes the design and execution of lesson plans, which are fundamental components of the program. These designs were based on the TPACK model (Mishra & Koehler, 2006), an educational framework that facilitates understanding of the relationship and intersection between technology, pedagogy, and content. As part of technological knowledge, participants were required to include appropriate technological tools or applications, which in this case were tools available in the maker laboratory. Pedagogical considerations involved the design, implementation, and evaluation of teaching and learning plans based on the maker pedagogical approach.

The present study employed a comparison between two distinct groups: the Non-AI group (n=59) and the AI group (n=55). The Non-AI group of participants developed their teaching and learning plans without the use of GenAI tools. In contrast, the AI group integrated GenAI into the second part of the planning process to enhance and optimize their pre-designed teaching and learning plans. It is noteworthy that the AI group used GenAI after completing their preliminary drafts, a strategy that enabled the preservation of their original ideas and facilitated critical reflection (Figure 1).

The prompts used with GenAI were primarily designed to assist trainee teachers in generating ideas and optimizing pre-designed teaching and learning plans. The following section presents a visual representation of the distinction between the two groups analyzed (Figure 1).

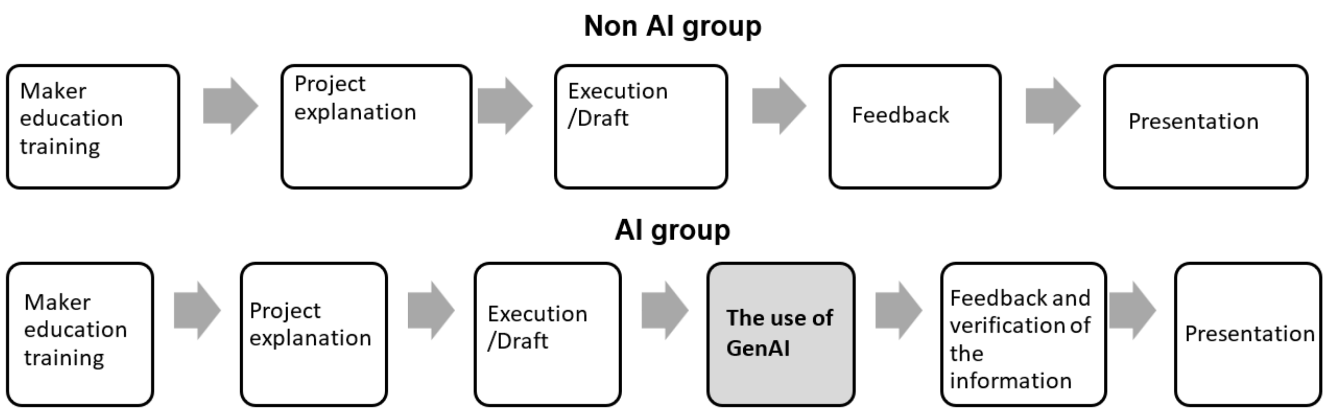

Figure 1. Representation of the distinction between the two groups analyzed.

2.2. Data Collection and Instrument

The data collection process was conducted after the training program, which was grounded in the maker pedagogical approach. This phase of data collection occurred after the presentation of participants' proposals to their respective classmates. It was emphasized to the participants that completing the questionnaire was voluntary and that their final grades would not be adversely affected by their responses. The questionnaire had two sections. The first section contained questions based on the Reduced Instructional Materials Motivation Survey (RIMMS), while the second section included items about the Technology Acceptance Model (TAM). The perceptions of pre-service teachers were measured using a Likert scale from 1 to 6.

The reduced version of the Instructional Materials Motivation Survey (RIMMS) was used (Loorbach, Peters, Karreman, & Steehouder, 2015), drawing on Keller's ARCS model of motivational design, which evaluates motivation through four subscales: attention, relevance, confidence, and satisfaction. Each subscale can be scored independently (Keller, 2010). The attention subscale includes items assessing the quality of the sessions (A3), the suitability of the assignment arrangements (A6), and the variety of assignments and illustrations (A10). The relevance subscale evaluates whether the content and materials are linked to what the learner has already learned (R1), as well as whether the content and materials are worthwhile, purposeful, and useful (R6 and R9). The confidence subscale measures how confident learners feel about understanding the content (C5), succeeding in assessments (C7), and how well the tasks are organized (C9). Finally, the satisfaction subscale assesses whether learners would like to explore further (S2), their enjoyment level of participating in the project (S3), and the pleasure derived from engaging with well-designed tasks (S6).

The Technology Acceptance Model (TAM) (Davis, 1989) was adapted to assess the acceptance of the maker pedagogical approach. In this research, this model is based on five dimensions: perceived usefulness (PU), perceived ease of use (PEU), perceived enjoyment (PEN), attitude towards use (ACU), and intention to use (IU). In this model, PU and PEU are critical, influencing users' overall attitudes, enjoyment, and intention to adopt the technology. The perceived usefulness subscale includes four items: learning improvement (PU1), facilitation of comprehension of specific concepts (PU2), overall usefulness (PU3), and enhancement of learning (PU4). The perceived ease of use subscale comprises three items: ease of use (PEU1), the absence of difficulties in learning and handling the tool (PEU2), and clarity in its use (PEU3). The perceived enjoyment subscale consists of three items: enjoyment of its use (PEN1), personal enjoyment (PEN2), and learning by doing (PEN3). The attitude towards use subscale, in turn, includes two items: the first item is to make learning more interesting (ACU1), and the second is that it is a good idea to use in class (ACU2). Finally, the intention to use subscale contains two items: intention to use in the future (IU1) and intention to use it to learn new topics (IU2).

2.3. Analysis of the Instrument

The study utilized both descriptive and differential statistics, in addition to correlational analysis, to ascertain the internal characteristics of each group. After compiling the data, the different sub-dimensions of each instrument were calculated. For both the RIMMS and the TAM, the means of the items corresponding to each sub-dimension and the total values of the instruments were calculated, resulting in the generation of average scores for individuals in each research group (Non-AI group – AI group). Subsequently, the assumptions of normality and homoscedasticity were verified. It was observed that all sub-dimensions presented non-normal distributions in both groups, except in the RIMMS of the AI group (Kolmogorov-Smirnov test, p=0.089). However, no significant differences were observed in the variability of any sub-dimension, with p-values greater than 0.05 in the Levene test, indicating equality of variances between the two groups. The instruments used in this study have been demonstrated to possess inherent reliability and validity, as evidenced by Cronbach's alpha values ranging from 0.797 to 0.967. This indicates a high degree of internal consistency among the sub-dimensions. The individual mean scores were re-scaled, resulting in the categorization of each score into one of four distinct categories based on numerical ranges. The Low (or Very Low) category includes values from 1 to 3, indicating a low or very low level. The Medium category covers the range 3 to 4, representing a moderate level. The High category includes values from 4 to 5, signifying a high level. Finally, the Excellent category falls within 5 to 6, indicating an excellent level.

This typology has been used to describe the characteristics of each group, aiming to identify percentage differences that can provide an initial overview of the results obtained through the methodology applied to each of the two student groups. Additionally, the varying proportions of their typological characteristics have been analyzed. Subsequently, a hypothesis test was conducted using the T-test to determine whether there are statistically significant differences in the means between the two study groups. The null hypothesis (Ho) states that there are no significant differences between the two groups of students in any of the sub-dimensions or in the overall measurements of the RIMMS and TAM instruments.

3. Results

3.1. Classification of Participants

The teacher training participants have been classified, in a preliminary manner, into different categories based on their scores. Each of these categories obtains percentage scores (Table 1), both in the overall calculation of the instrument on the motivation scale (RIMMS) and in the acceptance of technology (TAM).

The description of these percentages has been carried out on the contrast groups, both on vertical columns (AI group vs. non-AI group) and horizontal rows (categories or scale levels). At a general level, in terms of RIMMS, the sector of the sample (n=114) that shows motivation levels of both High (42.11%) and Excellent (24.56%) corresponds to 66.67% of the total sample, while the values for Medium (24.56%) and Low (8.77%) account for 33.33%. In terms of the overall percentage distribution of TAM, the scores in the High (44.74%) and Excellent (28.07%) categories represent 72.81% of the sample, while the proportions of Medium (16.67%) and Low (10.53%) ratings stand at 27.2%. This indicates a positive assessment of both instruments across the sample, with a majority of percentages rating very positively regarding motivation and acceptance of maker education.

Table 1. Percentages distributed by category of the RIMMS and TAM instruments.

		AI group (n=55)			Non-AI group (n=59)			Total (n=144)		
		n	**Row %**	**Column %**	**n**	**Row %**	**Column %**	**n**	**Row %**	**Column %**
RIMMS	Low	2	20.00	3.64	8	80.00	13.56	10	100.00	8.77
	Medium	12	42.86	21.82	16	57.14	27.12	28	100.00	24.56
	High	21	43.75	38.18	27	56.25	45.76	48	100.00	42.11
	Excellent	20	71.43	36.36	8	28.57	13.56	28	100.00	24.56
TAM	Low	3	25.00	5.45	9	75.00	15.25	12	100.00	10.53
	Medium	9	47.37	16.36	10	52.63	16.95	19	100.00	16.67
	High	19	37.25	34.55	32	62.75	54.24	51	100.00	44.74
	Excellent	24	75.00	43.64	8	25.00	13.56	32	100.00	28.07

However, these general positive proportions differ or change when the independent variable (Group) is introduced. An analysis of the levels of motivation (RIMMS) shows that, in terms of the sums of the percentages of the High and Excellent levels, there is a higher percentage concentration in the AI group (74.54%) than in the non-AI group (66.67%). Within the AI group, there is a tendency for the percentages to increase as the level of motivation rises, with a very low proportion at the Low level. Meanwhile, in the non-AI group, the maximum occurs at the High level (45.76%) but does not maintain the same intensity at the Excellent level, dropping more drastically to 13.56%. Regarding the horizontal distribution of motivation levels, within the Low level, 80% belong to the non-AI group, while 20% belong to the AI group. For the medium level, 57.14% of the sample in that category belong to the non-AI group, while 42.86% are in the AI group. At the High level, the proportions are 56.25% for the non-AI group and 43.75% for the AI group. Concerning the Excellent level, there is a reversal of the pattern observed at the Low level, as 28.57% belong to the non-AI group, while 71.43% are in the AI group.

The acceptance of technology (TAM) exhibits similar characteristics in terms of the percentage distribution across groups and categories. In vertical reading or columns of percentages, the AI group shows a consistent upward trend, ranging from the Low level (5.45%), Medium (16.36%), High (34.55%), to Excellent (43.64%). Conversely, the non-AI group reaches its highest percentage at the High level (54.24%) and declines at the Excellent level (13.56%). Notably, both groups have significant percentages between the High and Excellent levels, with the AI group achieving a higher percentage (78.19%) than the non-AI group (67.8%). In the horizontal percentages across rows, the Medium and High levels of TAM differ between the AI group (47.37% and 37.25%) and the non-AI group (52.63% and 62.75%), with the non-AI group holding higher proportions. However, an inversion occurs at the Low and Excellent levels: the AI group has lower percentages at the Low level (25%) compared to the non-AI group (75%), while at the Excellent level, the AI group accounts for 75% of the sample, whereas the non-AI group accounts for only 25%.

3.2. Statistical Analysis of the Instruments

Regarding the measurements collected for each of the instruments at a global level and in their sub-dimensions, a series of averages can be observed with a tendency towards the high category, especially among the group that has used AI when designing the teaching and learning plans (Table 2). In the case of the AI group, the RIMMS averages range from 4.39 points (Satisfaction) to 4.65 (Relevance), with the overall average for the instrument (4.51) indicating a high rating. As for the averages collected from the TAM instrument, higher scores are observed than in the RIMMS instrument, with ratings ranging from a minimum average (4.40) in the case of PEU to averages approaching excellent, as in the case of the ACU sub-dimension (4.71). Likewise, the overall score for acceptance of the TAM model (4.60) reflects a high rating for this instrument in the AI group.

Table 2. Statistics of the groups by subdimension and contrast test.

(Sub) dimension	Group		t-test for equality of means		d
	Non-AI (n=59) Mean (SD)	AI (n=55) Mean (SD)	t-test (*p*)	Mean difference	
Attention	3.92 (0.88)	4.50 (0.76)	<0.001***	0.58	0.68
Relevance	4.10 (0.98)	4.65 (0.89)	0.002**	0.55	0.58
Confidence	4.05 (0.92)	4.50 (0.89)	0.008**	0.46	0.50
Satisfaction	3.87 (1.08)	4.39 (1.03)	0.010**	0.52	0.49
RIMMS	3.98 (0.90)	4.51 (0.81)	0.001***	0.53	0.62
PU	4.06 (0.96)	4.69 (0.89)	<0.001***	0.63	0.68
PEU	3.88 (0.86)	4.40 (0.84)	0.001***	0.52	0.61
PEN	4.17 (1.09)	4.61 (1.05)	0.029*	0.44	0.41
ACU	4.21 (1.16)	4.71 (0.98)	0.015*	0.50	0.46
IU	4.08 (1.09)	4.62 (1.11)	0.011*	0.53	0.49
TAM	4.07 (0.92)	4.60 (0.85)	0.002**	0.53	0.60

Note: Equality of variances was assumed for all comparisons ($p > 0.05$ in Levene's test). *$p<0.05$; **$p<0.01$; ***$p<0.001$.

In contrast, the scores of the non-AI group obtained lower ratings, positioning them in the medium typology. Regarding the RIMMS instrument, average scores were obtained in some of its sub-dimensions, such as Attention (3.92) or Satisfaction (3.87). However, certain sub-dimensions achieved high scores, such as PEN (4.17) or ACU (4.21).

In general, regarding the RIMMS, the Non-AI group achieved an overall satisfaction score of 3.98, which is at the upper limit of the medium rating category. This indicates a specific difference of -0.53 compared to the AI group, which, as previously examined, achieved a high rating between 4 and 5 points (specifically, 4.51). Additionally, the Non-AI group, in its evaluation of the TAM instrument, provided average scores ranging from a medium rating of 3.88 in the PEU subcategory to the highest score of 4.21 in the ACU subcategory. Overall, the TAM score for this group is high at 4.07, but it is 0.53 points lower than the overall score of the AI group.

The comparison of the means obtained in both groups, through the T-test, indicates significant differences ($p<0.05$) between the means of both groups. A common pattern is characterized by the existence of significant differences between the two groups in all the sub-dimensions, as well as in the overall evaluations of both instruments. In the case of the RIMMS, there are highly significant differences ($p<.01$) between the mean values of the non-AI group and the AI group in all its sub-dimensions and in the overall calculation of the RIMMS. In the case of TAM, these differences are also highly significant; however, in the cases of PEN, ACU, or IU, they do not show such clear differences between the two groups analyzed. Nonetheless, in the overall case of TAM, the differences in means between them are highly significant ($p= 0.002$). The inclusion of Artificial Intelligence in the design phase of teaching and learning plans has had an average impact, with effect size values ranging from 0.41 to 0.68, with the highest values observed in Attention ($d=0.68$) and PU ($d=0.68$). It has also been observed that there is a medium effect in the acceptance of the technology ($d=0.60$), as well as a medium-sized effect ($d=0.62$) in motivation.

Thus, the significant differences between the two groups have been confirmed in all the sub-dimensions of the two measurement instruments, thereby rejecting the null or initial hypothesis. Significant differences were observed between the two groups analyzed. In principle, it can be stated that these differences may be attributable to the use of AI. If so, the hypothesis test confirms that the average scores on both instruments are significantly higher in the AI group than in the non-AI group.

4. Discussion and Conclusions

The vast majority of the literature to date has analyzed maker education from either a theoretical or practical perspective. However, there is still a lack of studies examining pre-service teachers' perceptions of maker education when incorporating other emerging technologies, such as Artificial Intelligence. In light of this limitation, the present study has explored the acceptance of maker technology and motivation towards it in two cases: with and without the use of AI.

In relation to the initial research question, the primary findings of the present study indicate that pre-service teachers who utilized GenAI demonstrated higher levels of motivation towards maker education across all subdimensions. Specifically, the AI group exhibited significantly greater attention, relevance, confidence, and satisfaction compared to their non-AI counterparts. These results suggest that AI support may have the capacity to enhance various motivational factors, aligning with previous research which found that AI tools positively influence motivation and may lead to improved learning outcomes in educational settings (Mohamed, Shaaban, Bakry, Guillén-Gámez, & Strzelecki, 2024).

The second research question targeted the differences in acceptance of technology, and it can be concluded that the results were similar to the previous paragraph, with the group of teachers who had worked with generative AI demonstrating a higher level of acceptance in all the sub-dimensions that were analyzed. This heightened level of acceptance aligns with the findings of other studies that have examined the acceptance of technology, particularly artificial intelligence, among pre-service teachers (Zhang, Schießl, Plößl, Hofmann, & Gläser-Zikuda, 2023). The perceived usefulness (PU) sub-dimension revealed the most significant differences, with the dimensions of intention to use (IU) and perceived ease of use (PEU) ranking second and third, respectively. This observed level of acceptance may be attributed to studies that have previously analyzed the acceptance of chatbots by students (Ragheb, Tantawi, Farouk, & Hatata, 2022) and their impact on student success (Chen, Jensen, Albert, Gupta, & Lee, 2023). However, it has also been analyzed that when planning, the designs of scientific units created by artificial intelligence should be critically evaluated and adapted to their particular teaching contexts (Cooper, 2023). The high intention to use it that pre-service teachers have demonstrated in this study is consistent with the research conducted by Lozano and Blanco Fontao (2023), which found positive perceptions of pre-service teachers when using AI.

5. Limitations and Future Lines of Research

The present study is subject to several limitations, the most notable of which is the sample size, which is limited to a particular degree, that of teacher training. Furthermore, the context in which this research has been carried out is limited. It is recommended that future research replicate this study in the in-service setting to expand and contrast the results. Another limitation is that only a post-test was analyzed; including a pre-test might have provided additional valuable insights into the results.

Moreover, the present study is restricted in scope to the description of a comparative study between two groups, without any experimental examination of the underlying causes. It is recommended that future research investigate the factors that lead to increased motivation for maker education and higher technology acceptance when AI is integrated, and such questions could be effectively researched using qualitative research methods.

Despite the limitations identified in this study, it is expected to provide valuable insights into how teachers perceive the integration of AI in higher education, thereby contributing to a more comprehensive understanding of these emerging technologies.

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