Acceptability of technology involving artificial intelligence among future teachers

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Abstract

Technology has been used in the service of learning for a long time. Nowadays, the use of Artificial Intelligence (AI) is developing but its acceptability among future teachers still needs to be investigated. Moreover, differences between elementary and middle-school teachers could arise, due to the comparison between their role and those of technology involving AI. The current study aims at evaluating the acceptability of technology involving AI among future teachers, using a well-known model and more specifically regarding several tasks. Results show that elementary school teachers expect more performance from technology involving AI, but mainly for a use of content generation (e.g., course content, exercises). Middle-school teachers are more willing to accept technology involving AI for more high added value tasks such as help in writing learning or in diagnosing learning difficulties. Future studies should focus on identifying action levers to favor higher acceptability and actual use.

Keywords: Education; Artificial Intelligence; Acceptability

Theoretical background

Teaching machines involving AI

The use of technology for educational purpose is not a recent idea. A hundred years ago, Pressey, and then Skinner, invented teaching machines. According to a description made by Skinner himself (1958), the machine by Pressey presented questions and, for each question, several possible responses. Learners had to press the button corresponding to the response they chose. If they chose the correct answer, another question was proposed, and so on. If the answer was incorrect, learners had to choose another response until they found the correct one. The machine by Skinner was slightly different: learners did not recognize the correct answer among those proposed, but they had to write it. These exercisers, conceived in the context of behaviorist learning, had the benefit to propose immediate feedback after the response choice and difficulty-adapted questions. The final objective was to individualize learning, by respecting the rhythm and needs of each learner (Watters, 2021).

Nowadays, technologies for learning can take different forms, such as multimedia documents, videos, or virtual reality. The objective is always to enrich learning situations. Indeed, technologies can help teachers to facilitate learning process by providing content that respect some design principles (e.g., modality effect, Ginns, 2005; signaling or contiguity principles, Mayer & Fiorella, 2014). Moreover, the technical limitations of the last century are no longer relevant today. The use of Artificial Intelligence (AI), and particularly machine learning, is developing in the educational field, with the possibility of generating content (e.g., summaries, subtitles in videos from oral content, Cojean & Martin, 2021) or analyzing several variables (i.e., learning analytics, Nistor & Hernández-Garcíac, 2018). Currently, learning softwares (e.g., Pensum, Loiseau et al., 2011; KidLearn project, Oudeyer et al., 2020; ProVoc, Potocki et al., 2021; TACIT, Quaireau et al., 2016) can be considered as the natural evolution of teaching machines, even if they are sometimes far from behaviorist exercisers. These software, generally designed to enhance the acquisition of one specific skill (e.g., document summaries drafting, numeracy, vocabulary learning, implicit comprehension), allow to consider individual differences and personalize learning (De Lièvre et al., 2019). Thus, they represent an important learning support that teachers could use. However, one of the major topics when investigating the use of AI for educational purpose remains the relationship between the teacher and the machine (Pu et al., 2021). An analysis of the intention to use educational technology involving AI seems therefore necessary.

Acceptability

Several theoretical models (e.g., Technology Acceptance Model (TAM), Davis et al., 1989; Unified Theory of Acceptance and Use of Technology (UTAUT), Venkatesh et al., 2003) can be solicited to evaluate acceptability (i.e., judgment towards a product or a system before use, Schuitema et al., 2010) of new technologies. On the basis of these models, some studies have already been conducted on the evaluation of AI acceptability in professional (e.g., Martin et al., 2020) or educational context (e.g., Cruz-Benito et al., 2019; Gado et al., 2021). In these studies, models on the adoption of one product or system (e.g., mobile app) have been adapted to the evaluation of a concept as broad as AI. It has notably been showed that the classical acceptability/acceptance models are still relevant to apply to AI (e.g., Martin et al., 2020), with several variables supposed to have an impact of future use of technology involving AI:

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performance and effort expectancy, social influence, and facilitating conditions.

The role of the resistance to change is also mentioned (Cruz-Benito et al., 2019), probably related to the regularly expressed fear of machines replacing humans. Indeed, the "algorithm aversion" (Mirbabaie et al., 2021) refers to the perceived threat that jobs disappears in favor of AI. However, since the invention of the first teaching machines one hundred years ago, Skinner (1958) claimed that machines would not replace teachers, but rather discharge them from costly tasks.

Overall, the use of technology by teachers is not acquired. In France, according to official reports (PROFETIC, 2018, 2019), more than 90% of teachers use digital technologies to create content, more of 80% use digital technologies in class, but this percentage goes down to 57% (middle-school teachers) and even 40% (elementary school teachers) for a use involving manipulation from learners. These differences of use between elementary and middle-school teachers may be the resultant of a greater perceived threat for elementary school teachers. Indeed, the later would be more task-focused, whereas middle-school teachers would be more performance-focused (Midgley et al., 1995). Using technology to improve students' performance would then be considered as a useful tool for middle-school teachers (i.e., it would help them achieve more easily the performance-focused goal), but elementary school teachers would fear much more to be replaced in their job contribution (i.e., students support). Besides, a recent study (Backfisch et al., 2021) showed that perceived utility of technology would be a major factor of its use.

Current study

The aim of the current study is to investigate the acceptability of learning technologies involving AI among future teachers. Elementary school teachers use less technologies in class than middle-school teachers and the fact that they are task-focused (Midgley et al., 1995) may increase the perceived threat of technology replacing them. Indeed, helping students may be considered as their role and final aim, more than the performance itself. Middle-school teachers, more focused on performance, would accept more easily technology to enhance it. Then, the main hypothesis is that elementary school teachers would have a lower acceptability than middle-school teachers. More precisely, we hypothesize that:

H1. Elementary school teachers would have lower scores on the UTAUT variables than middle-school teachers.

H2. Elementary school teachers would be more reluctant than middle-school teachers to use different applications of technology involving AI in their daily work.

Methodology

Participants

A questionnaire was sent via Internet to French future teachers in master degree. A total of 406 participants (282 women, 122 men, 2 responded "other", Mean age = 25.63, SD = 6.91) responded, 213 in elementary school formation, 193 in middle-school formation. All of the participants volunteered to take part to the study, signed a consent form, and the experiment was conducted in accordance with the principles of the Declaration of Helsinki (World Medical Association, 2013).

Material and procedure

The questionnaire was divided in four parts. Firstly, a definition of AI was proposed, to make sure that participants had the same information before to respond: "Artificial intelligence is concerned with the development of computers able to engage in human-like thought processes such as learning, reasoning, and self-correction" (Kok et al., 2009). In the second part of the questionnaire, participants had to position themselves on 11-points Likert scales (from 0 to 10) related to UTAUT (Venkatesh et al., 2003) variables (three items per dimension): performance expectancy (e.g., "I think that artificial intelligence could be useful in my courses"), effort expectancy (e.g., "Learning how to use technology involving artificial intelligence would not be difficult for me"), social influence (e.g., "I would use technology involving artificial intelligence if my colleagues use it too"), facilitating conditions (e.g., "The use of technology involving artificial intelligence is compatible with my experience with other technologies"), intention to use (e.g., "I will use technology involving artificial intelligence in my courses as soon as I can"). Two items evaluating prior experience with new technology and AI were also proposed (e.g., "I feel comfortable with the use of new technology"). The third part of the questionnaire was composed of a list of pedagogical tasks that technology involving AI might support (e.g., "Artificial intelligence could be useful to generate math of French exercises"). In the tasks proposed, AI might be used to generate content, provide personalized feedbacks, or analyze strategies and performance in real-time. For each task, participants had to indicate on 11-point Likert scales (from 0 to 10) how much they think AI could be useful in these cases. Finally, participants completed demographic questions about their age, gender, and master degree specialty (i.e., elementary or middle-school teachers).

Results

The differences between the two experimental groups (i.e., elementary school and middle-school teachers) were analyzed using ANalyses Of VAriance (ANOVA) with a significance level set at $\alpha = .05$. The effect size was evaluated using partial eta squared η^2.

Prior experience

Prior experience in the use of technology was considered as a control variable. According to their responses on Likert scales, all of the participants had a score of "prior experience" from 0 to 10. ANOVA revealed no significant differences between the two groups, $F(1, 404) = 0.63$, $p = .428$, $\eta^2 = 0.00$ (see Table 1 for descriptive statistics).

Table 1: Descriptive statistics for prior experience.

	Elementary school teachers		Middle-school teachers	
	M	SD	M	SD
Prior experience	5.30	2.38	5.11	2.61

Acceptability of technology involving AI (UTAUT)

ANOVAs revealed a significant effect of experimental condition on performance expectancy ($F(1, 404) = 4.40$, $p = .037$, $\eta^2 = 0.01$). According to descriptive statistics (see Table 2), elementary teachers perceived technology with AI as more useful than middle-school teachers.

No significant effect was found between the two groups concerning effort expectancy ($F(1, 404) = 0.09$, $p = .763$, $\eta^2 = 0.00$), social influence ($F(1, 404) = 0.55$, $p = .460$, $\eta^2 = 0.00$), facilitating conditions ($F(1, 404) = 0.07$, $p = .796$, $\eta^2 = 0.00$), or intention to use ($F(1, 404) = 2.94$, $p = .087$, $\eta^2 = 0.01$).

Table 2: Descriptive statistics for UTAUT variables.

	Elementary school teachers		Middle-school teachers	
	M	SD	M	SD
Performance expectancy	5.08	2.21	4.59	2.50
Effort expectancy	4.47	2.17	4.40	2.30
Social influence	4.51	2.20	4.35	2.36
Facilitating conditions	4.65	2.05	4.59	2.25
Intention to use	3.87	2.4	3.45	2.52

Acceptability of tasks AI can support

ANOVAs revealed a significant effect of experimental condition on creation of course support or content ($F(1, 404) = 6.13$, $p = .014$, $\eta^2 = 0.01$), generation of math or French exercises ($F(1, 404) = 5.26$, $p = .022$, $\eta^2 = 0.01$), help in learning writing ($F(1, 404) = 4.22$, $p = .041$, $\eta^2 = 0.01$), and help to the diagnostic of learning difficulties ($F(1, 404) = 8.87$, $p = .003$, $\eta^2 = 0.02$) acceptability.

Descriptive statistics (see Table 3) indicate that elementary school teachers are more willing to accept technology involving AI for the creation of course content and exercises, but middle-school teachers are more willing to accept technology involving AI for help in learning how to write and to the diagnostic of learning difficulties.

No significant effect was found between the two groups concerning help in learning foreign languages ($F(1, 404) = 2.02$, $p = .156$, $\eta^2 = 0.00$), proposing exercises with adapted difficulty ($F(1, 404) = 0.11$, $p = .740$, $\eta^2 = 0.00$), or real-time corrections ($F(1, 404) = 0.38$, $p = .537$, $\eta^2 = 0.00$) acceptability.

Table 3: Descriptive statistics for acceptability of tasks involving AI.

	Elementary school teachers		Middle-school teachers	
	M	SD	M	SD
Creation of course support or content	6.10	2.66	5.41	2.95
Generation of math or French exercises	6.56	2.48	5.95	2.83
Help in learning foreign languages	6.54	2.42	6.16	2.89
Help in learning how to write	4.40	2.78	4.99	3.01
Proposing exercises with adapted difficulty	6.22	2.61	6.12	2.94
Real-time corrections	4.86	2.97	5.04	2.97
Help to the diagnostic of learning difficulties	5.23	2.75	6.04	2.74

Discussion

The aim of the current was to investigate acceptability of technology involving AI among future elementary and middle-school teachers. We hypothesized that middle-school school teachers would be more likely to accept and use technology involving AI in class, mainly because it would be less threatening for them. Conversely, elementary school teachers would represent their job as more task focused, implying more importance to human support, so they would represent technology involving AI as a threat of replacement.

Results one the UTAUT variables are surprising. Performance expectancy is higher for elementary school teachers. No differences are observed between elementary and middle-school teachers on effort expectancy, social influence, facilitating conditions or intention to use. These results seem contradictory to previous data indicating that elementary school teachers use less digital technology than middle-school teachers in class (PROFETIC, 2018, 2019).

More specifically, acceptability differs depending on the task that technology involving AI could support. Elementary school teachers seem more willing to accept the help from technology involving AI for the generation of course content or exercises. These tasks generally take place during course preparation (i.e., before the class), and are not directed to interaction with or between students. This is therefore congruent with the high use of digital tools to create content but lower use in class with manipulation by students (PROFETIC, 2018, 2019). Middle-school teachers seem more willing to accept the help from technology involving AI for assisting students during writing learning and for detecting potential learning difficulties. These tasks can be usually considered as specific to the student-teacher interaction, and so delegate them to AI could represent a bigger threat for elementary school teachers. Middle-school teachers, who seem to be more focused on performance, may consider that every help is beneficial to achieve this goal, even the help from AI.

Eventually, the current study sheds the light on the disparity among future teachers on acceptability towards new technology. Future studies should focus on identifying action levers to favor higher acceptability and actual use. These levers (e.g., deep understanding of AI functioning) could be different among populations (i.e., elementary or middle-school teachers).

Future studies should also prevent some limits of the current study. Men and woman are not equitably distributed among conditions (i.e., 25 men and 188 women for elementary school teachers, 97 men and 94 women for middle-school teachers). This may reflect the actual repartition between elementary and middle-school teachers but could be considered. Although we had no hypothesis on a difference according to gender, when taken into account, results on the UTAUT variables show a significant impact of gender ($F(2, 401) = 5.83$, $p = .003$, $\eta^2_p = 0.00$), with higher scores for men than women, and a significant interaction between condition and gender ($F(1, 401) = 4.72$, $p = .030$, $\eta^2_p = 0.00$) on effort expectancy. Finally, on variables with significant differences between conditions, effect sizes vary between 0.01 and 0.02, which is considered as a small effect. Results should be interpreted with caution regarding this issue.

At the beginning of the questionnaire, a definition of AI was proposed, to make sure that all of the participants had the same definition in mind when answering. However, this might not be sufficient, because they could have previous representations (Ragot et al., 2020). It may be interesting to question these previous representations to adapt the proposed definition, and correct inaccurate perceptions for example. Finally, examples of tasks proposed to evaluate acceptability more precisely could be reconsidered. They could be more detailed and provide more ecological scenarios.

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