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A Grade for Artificial Intelligence: A Study on School Teachers' Ability to Identify Assignments Written by Generative Artificial Intelligence

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Abstract

Artificial intelligence (AI) is rapidly advancing across various sectors, including education. However, AI in education raises ethical concerns, for example, regarding the originality of students' homework, which could affect both learning outcomes and student–teacher's trust. Despite AI's potential benefits, many teachers feel skeptical about its use, fearing that students may use it unfairly. This study aims to explore teachers' ability to assess the originality of student assignments and identify AI-generated content, taking into consideration teachers' expertise, self-efficacy, and personality. A sample of 67 middle and high-school teachers evaluated six short assignments, half written by real students and half by AI (ChatGPT 3.5). *t* Tests and analysis of variance were conducted to compare the identification accuracy of assignments and the relationship with teachers' expertise, and regressions were performed to examine the relationships between identification accuracy, personality traits, and self-efficacy in detecting originality. Teachers were able to identify AI-generated assignments but struggled with student-generated ones. Furthermore, teachers with more expertise exhibited a potential bias against students, mistakenly identifying their work as AI-generated. While teachers were able to evaluate assignments objectively, openness and conscientiousness predicted their self-efficacy in assessing originality. We discuss how educators may learn new opportunities to use generative AI to promote learning and engagement. Although students may leverage AI to minimize their workload, AI represents a way to support them during the learning process, if it is developed taking into account students' and teachers' needs and characteristics.

Keywords: education, artificial intelligence, teachers, personality, cheating

Introduction

Artificial intelligence (AI) has been finding a large space in the education sector in recent years,[1] reshaping some educational practices and teaching activities.[2,3] However, its acceptance depends above all on the attitudes of its users,[4,5] who, despite recognizing the effectiveness of AI, are skeptical about its use by students who might employ it unethically—for example, by asking it to write essays on their behalf.[6] Certainly, AI offers personalized and scalable approaches to education[7,8] and also redefines knowledge assessment. In Zhai et al. review of AI's educational tools and applications,[9] there is a reinforcement of the concept, where we can read the increasing integration in education, especially as a tool to promote adaptive learning, to give personalized feedback to students, to support them as an intelligent tutoring system.

When a new technology is introduced into schools, it consistently sparks debates that can be viewed in a dichotomous way, that is, by techno-enthusiasts and by technophobes. This has also been the case with ChatGPT, which has reignited discussions around the risks and opportunities brought about by technological innovation in educational settings. A recent SWOT analysis[10] highlights the perspectives of those who view the tool as a positive resource, considering it a truly adaptive learning environment,[11] while others emphasize the negative impacts on assessment practices,[12] scientific integrity,[13,14] and ethical concerns.[15] Furthermore, studies have examined the negative impact that tools such as ChatGPT

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may have on students' higher-order thinking skills.[16] However, as noted in the mentioned SWOT analysis, a comprehensive overview that could establish a theoretical basis for empirical studies aimed at harnessing the potential of this new AI technology is still lacking.[10] The results of this analysis can be summarized as follows (Fig. 1).

A human-centered approach is required for the proper introduction of AI in schools. This could start from a better understanding of how AI is perceived by users, both in the social context and specifically within educational settings. Studies have shown that personality traits can influence attitudes toward AI—for example, people with higher levels of agreeableness and conscientiousness tend to have a more positive attitude toward it.[17,18]

To gain a deeper understanding of individual attitudes toward AI, it is crucial to examine perceptions of AI-generated content, especially considering the uncertainty regarding its authenticity. The research shows that people are generally incapable of distinguishing AI from human-generated content, especially text-based material.[19,20] When facing the possibility that a content has been generated by AI, people tend to have negative attitudes toward it, especially when authenticity is expected.[21] For example, people tend to dislike art made by AI,[22] while they could be more positive toward content devoted to mere entertainment where the role of AI is declared.[23] Many today are also aware that AI-generated content may be biased or misleading and, in an era where technology-mediated content is often deemed unreliable (e.g., fake news), tend to harbor suspicion toward it.[24,25]

Regarding the educational context, several studies have raised concerns about the infiltration of AI tools in university systems, highlighting the need for educators to ensure academic integrity by being able to identify AI usage. For example, Scarfe et al.[26] injected AI-written submissions into the examinations system in five undergraduate modules and found that the submissions were not detected and received higher grades than regular human-made submissions. However, this study did not consider examiners' perspective nor psychological factors that could impact their assessment of assignments.

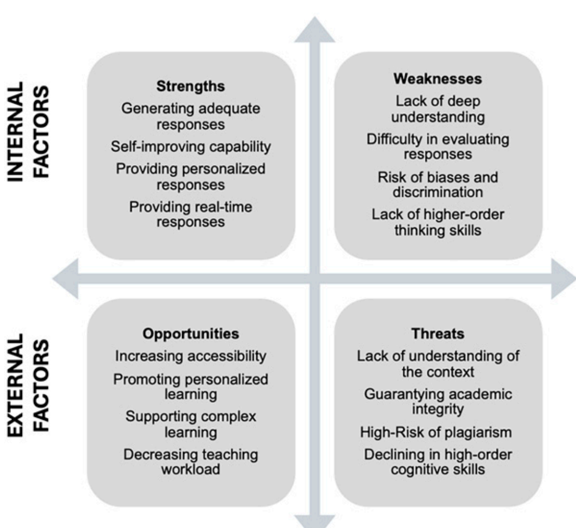

FIG. 1. SWOT analysis on the use of ChatGPT in education (adapted from Farrokhnia et al.[11]).

Studies show that teachers usually have a negative attitude toward students' cheating, although they distinguish different types of cheating as more or less serious and can empathize with some of the cheating students' motivation.[27]

On the contrary, teachers' attitude toward students' conduct (including cheating), as well as their personality, may affect their educational style and the severity by which factual or potential issues are addressed: For example, conscientiousness, neuroticism, stress, and burnout all play a role in teachers' appraisal of students' behavior and subsequent decisions for referral.[28]

Recent studies addressed cheating with AI specifically. Early data collected when tools such as ChatGPT became widespread revealed that teachers were substantially unsure about the difficulty to assess whether assignments were student or AI-made, and cautious when assessing their own understanding of the technology.[29] By applying qualitative methods, Mah et al.[30] found that students and teachers came to different conclusions when reasoning about learning and cheating with generative AI, especially students were more lenient and considered some dubious behaviors as "scaffolding" rather than "taking a shortcut." Consistently, studies on anonymous students who report on their cheating behavior found that the perception of cheating has not sensitively changed after the introduction of AI tools: Students consider some "partial" uses (e.g., asking a chatbot to write just a part of an assignment) less problematic than doing the same with traditional sources.[31] The literature does not offer a clear understanding of how capable teachers feel in distinguishing between student and AI-generated work. Concerns have led some teachers to avoid using AI altogether.

As said above, teachers' attitudes and personalities may play a role in teachers' attempt to identify assignments written by AI or human students, possibly affecting the objectivity of judgment. There is indeed evidence that personality traits[32] and confidence[33] could influence the actual ability to identify dishonest behavior and lie, as well as the conviction of being more or less proficient in doing it (self-efficacy).

For example, several studies have shown that people high in manipulation and self-monitoring are more effective in lie detection.[34,35] Furthermore, some research has revealed that specific groups such as secret services, police officers, and even criminals have a greater ability to detect lies.[36] These present some distinctive personality characteristics such as extraversion, authoritarianism, exhibitionism, conservatism, suspiciousness, and aggressiveness.[37,38]

In general, conscientious people are more attentive, observational and are likely to obtain better performance in many tasks.[39] Consistently, given that mastery, vicarious experience and persuasion are the main sources of self-efficacy,[40] open-to-experience individuals have more opportunities to engage in new experiences that can feed their beliefs about their own abilities, while extraverted individuals may encounter more social opportunities for vicarious experiences and persuasion.

In contrast, higher expertise in teaching may allow teachers to identify subtle features of assignments useful to address their originality. Already 20 years ago, Williams[41] reported that teachers experienced difficulties in detecting cheating during the information technologies era; however, those with more experience were able to come up with methods for ensuring verification. Consistent with existing research,[42–46] this study will explore how teachers' personality traits[47,48] and professional expertise[49] shape their attitudes, self-efficacy, and ability to critically identify human or AI-generated content. The aims of the study could be resumed in the subsequent research questions:

RQ1: Can teachers identify assignments written by human students versus AI?
RQ2: Do teachers' personality traits influence ability and self-efficacy in their assessment of originality of assignments?
RQ3: Do teachers' expertise influence ability and self-efficacy in their assessment of originality of assignments?

Materials and Methods

Participants and procedure

Sixty-seven Italian school teachers (52 females, 1 prefer not to say, mean age = 44.18, standard deviation = 10.6, min = 25, max = 68) from middle ($N = 20$) and high schools ($N = 47$) were recruited to participate in an online survey through Qualtrics. The teachers in the sample reported having previously used ChatGPT or similar ($N = 30$) and having employed any AI tool for teaching purposes ($N = 23$, essentially for creating images and searching information). The participants were invited *vi*a mailing list to take part in this study. We used snowball sampling based on respondents' and researchers' networks.[50] All the participants consented to participate voluntarily and did not receive incentives for their participation. Data were collected from February to May 2024. Informed consent was obtained prior to the questionnaire completion and anonymity was protected for all participants. Ethical approval was obtained from the Ethical Committee of Università Telematica Pegaso.

Measures

After having provided sociodemographic information, participants were asked to answer questions about their professional background. Specifically, they reported working as teachers for less than 3 years, 4–7 years, 7–12 years, or more than 12 years. Moreover, they reported their main teaching subject. These variables were configured this way due to characteristics of the teaching profession in Italy: teachers may have developed experience before obtaining an official position and also may teach more than one subject at the same time (e.g., history and language/literacy). After that, participants were invited to respond to self-report questionnaires:

- The Big Five Inventory[51,52] assesses personality traits through 44 items. It explores five dimensions of personality: Openness to experience, such as curious, imaginative, and artistic people; Conscientiousness, such as efficient, organized, and thorough people; Extraversion such as sociable, energetic, and enthusiastic people; Agreeableness such as forgiving, warm, and sympathetic people; and Neuroticism, such as tense, irritable, and moody people. Items are assessed on a 5-point scale ranging from "strongly disagree" to "strongly agree." Reliability indexes were satisfactory, extraversion: 0.76, agreeableness: 0.62, neuroticism: 0.75, conscientiousness: 0.81, and openness to experience: 0.78.
- Likert scale from 0 to 100 (0 = not at all able; 100 = perfectly able), to two *ad hoc self-efficacy questionnaires*, designed according to the typical recommendations for the construct.[53] The first one investigated the ability to recognize the originality of a student's work, while the second one the ability to distinguish a work created by AI. Specifically, teachers were asked to evaluate the originality of a student's work (i.e., to notice if a student's work has been copied from other sources, e.g., a textbook or another classmate's work), and, subsequently, how much they think they are able to distinguish a written work done by a student from one generated by an AI, in all these situations: homework, class test, open-ended questions, multiple-choice questions, and group work.
- Finally, teachers were asked to give their opinion using a Likert scale from 1 to 10 (1 = "not at all agree," 10 = "completely agree") to a number of statements regarding six short assignments from different disciplines (e.g., history, geography, science, and literacy), half written by students and half by AI (ChatGPT 3.5) (for the assignments' text, see Supplementary Appendix). The assignments featured a brief question and the student/AI's response, and they were made to be roughly the same length. ChatGPT 3.5 was also instructed to provide the assignments such as it was a human student of the appropriate age. The items regarded the source of the assignment (i.e., "*This answer has been written by a human student*" and "*This answer has been written by AI*"); the teachers were also asked to provide a 1–10 grade to each assignment ("*Give a grade to the response from 1 to 10 in terms of correctness, clarity, completeness such as it was an actual assignment by a student*").

Results

In order to address the main research questions, eight new variables were computed, as described in Table 1. These variables represent average scores from participants' responses when they were trying to attribute any assignment text to human students or AI: they can be grouped in correct identification (AI–AI and human–human, respectively averaged attributions of AI texts to AI or of human texts to humans) and incorrect identification responses (human–AI and AI–human, namely human texts attributed to AI and the opposite). Furthermore, we computed two variables reflecting participants' beliefs about their ability to identify original student versus AI assignments (self-efficacy), and two variables representing average grades given to assignments made by students versus AI.

To respond to RQ1, in order to test whether there was a difference between the correct identification of AI and human assignments, we performed a series of paired-sample t tests between the first four variables related to correct/incorrect identification of human-/AI-made responses (Fig. 2). Only the comparison between AI–AI and AI–human was significant (namely correct vs. incorrect identification responses pertaining to AI-made assignments), highlighting that teachers tended to correctly identify AI-made answers.

To respond to RQ2, we performed four regression analyses with personality traits as predictors and the four variables related to correct/incorrect identification of human-/AI-made responses; the regressions were not significant, highlighting that personality traits seem not to play a role in the identification of human-/AI-made responses.

Table 1. Description of the Variables Used in the Study

Name of variable	*Variable description*	*Variable meaning*
Human–human	Mean of the responses to item "this assignment has been written by a human student" for the assignments that had been written by a human student	Correct identification of human students' assignments
Human–AI	Mean of the responses to item "this assignment has been written by AI" for the assignments that had been written by a human student	Incorrect identification of human students' assignments as written by AI (AI bias)
AI–human	Mean of the responses to item "this assignment has been written by a human student" for the assignments that had been written by AI	Incorrect identification of AI assignments as written by human students (human bias)
AI–AI	Mean of the responses to item "this assignment has been written by AI" for the assignments that had been written by AI	Correct identification of AI's assignments
Self-efficacy originality	Mean of the responses to the items "how confident are you in your ability to identify the originality of students' made homework/classwork/open question/closed question/group work"	Teachers' self-efficacy related to the ability to identify original students-made work
Self-efficacy AI-made	Mean of the responses to the items "how confident are you in your ability to identify homework/classwork/open question/closed question/group work that have been actually written by AI"	Teachers' self-efficacy related to the ability to identify work written by AI
Human grades	Mean of the grades given by teachers to human students' assignments	Evaluation of human students' work
AI grades	Mean of the grades given by teachers to AI-made assignments	Evaluation of AI-made work

AI, artificial intelligence.

Then, we performed two regression analyses with personality traits as predictors and the two variables self-efficacy originality and self-efficacy AI made: the first one was significant ($F = 5.695$, $p = 0.000$) and explained 35 percent of the variance. Specifically, openness to experience ($\beta = 0.320$, $p = 0.029$) and conscientiousness ($\beta = 0.375$, $p = 0.015$) predicted self-efficacy originality.

Finally, after creating a two-level variable based on years of experience, to respond to RQ3, we performed analysis of variance with high/low teaching experience as the independent variable and human–human, human–AI, AI–human, AI–AI, human grades, and AI grades as dependent variables (Table 2). The results showed that teachers with more years of experience were more likely to both identify AI-written assignments and attribute human students' assignments to AI. Moreover, teachers with more experience assigned higher grades to human students' assignments.

Discussion

The present study addressed the issue of school assignments' originality related to students' utilization of AI resources from the point of view of middle and high-school teachers. The objective was to explore teachers' attempts to identify assignments written by human students or AI, their self-efficacy regarding the ability to assess originality versus AI utilization by the students, and the relationship between these variables and teachers' personalities and expertise.

Results from the first analysis showed that teachers were able to correctly distinguish AI-made assignments; however, the same did not emerge for what regards human-made assignments which were not significantly distinguished from work made by AI. It is possible that experienced teachers can detect subtle aspects in language utilization, sentence structures, organization of topics within an assignment as nontypical of students but rather of what an AI language model would produce. However, at the same time the originality of human students' work may be more difficult to identify. This could be possibly related to teachers' caution toward a technology they feel they still do not understand in full. That said, this analysis alone may be considered questionable, as teachers in the sample-assessed texts with different contents not necessarily related to their expertise and indeed the average scores may not reflect their proficiency with each stimulus: one could observe that the means of the four variables are quite similar despite the significant difference. However, consistently the analysis based on expertise revealed that more experienced teachers not only were more correct in identifying AI-made assignments but also tended toward false positives, attributing human students' work to AI. This result may point toward the existence of an "AI bias" or the conservative tendency to detect the utilization of AI where it was absent. The relationship with years of experience may be related to older teachers harboring more suspicious attitudes toward new technologies and AI, due to stronger resistance to change.[54,55] An alternative, more subtle interpretation would take into account that higher expertise could sometimes distort cognition,[56] such as in hindsight bias (i.e., the inaccuracy when assessing one's own predictions): teachers who reported

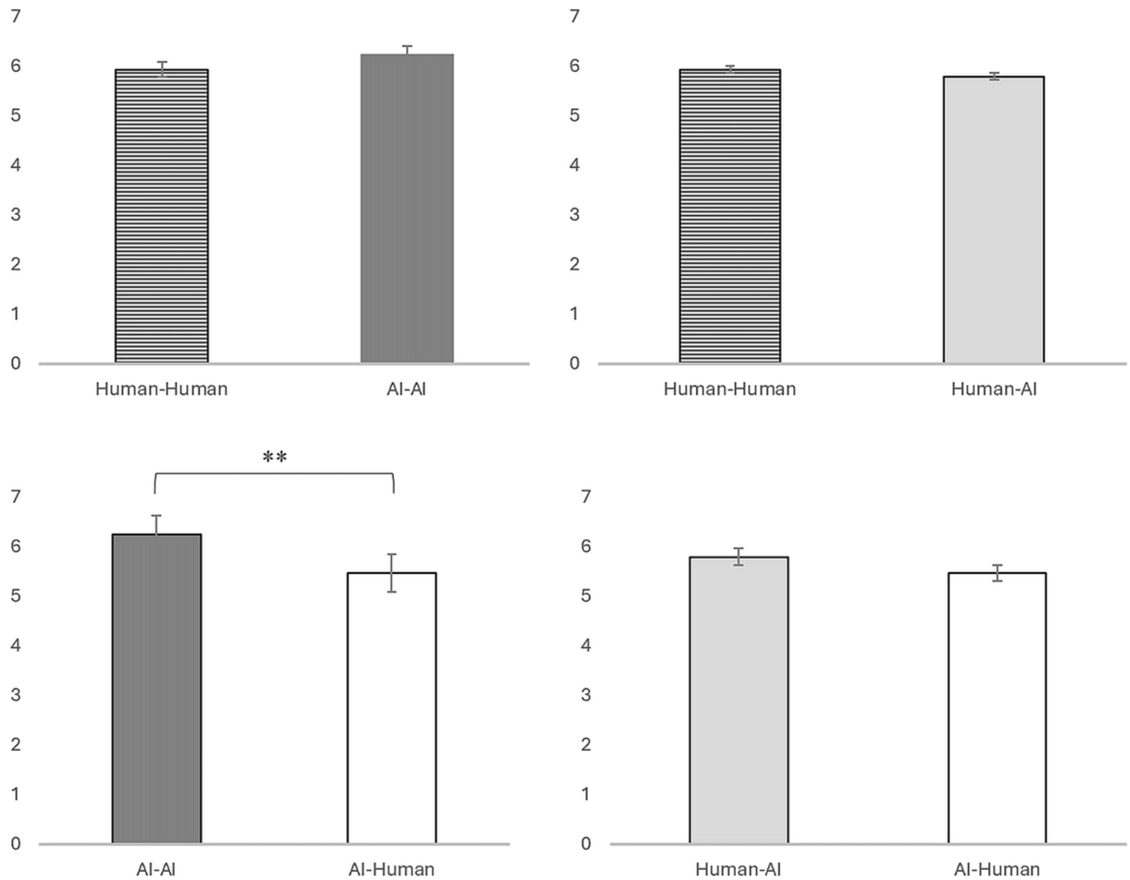

FIG. 2. Comparisons between teachers' judgments of assignments' originality or AI origin.

higher expertise may have been more motivated to not be "fooled" by AI and therefore were more likely to lean toward suspicion when evaluating the assignments.

That said, it is interesting to notice that more experienced teachers, independently of correctly identifying them, were also more likely to give higher grades to authentic human-made assignments. While this result would certainly need further investigation, one could speculate that human students-made assignments had subtle features in content and structure that moved more experienced teachers to recognize the authenticity of human students' efforts. In contrast, novice teachers may have been more cautious both in attributing assignments to humans or AI and in assigning grades, possibly revealing less confidence in dealing with the risk of AI cheating. This may point toward the necessity to develop formation resources for teachers that consider individual knowledge, confidence, and level of expertise, in order to properly equip education professionals to deal with the challenges of AI utilization within the educational processes.

The fact that personality traits did not appear to play any role in the tendency to attribute assignments to human students or AI (either correctly or incorrectly) could be considered a positive result in terms of teachers' professionalism: teachers in our sample were not influenced by their

Table 2. Analysis of Variance Based on Teachers' Expertise

Variable	*Analysis of variance*	*Mean and SD*
Human–human	$F = 1.221$, $p = 0.275$, eta squared = 0.026	Teachers with less experience: 5.72, 1.43 Teachers with more experience: 6.22, 1.66
Human–AI**	$F = 7.592$, $p = 0.008$**, eta squared = 0.142	Teachers with less experience: 5.24, 1.77 Teachers with more experience: 6.52, 1.31
AI–human	$F = 2.624$, p = 112, eta squared = 0.054	Teachers with less experience: 5.14, 1.5 Teachers with more experience: 5.9, 1.72
AI–AI**	$F = 7.913$, $p = 0.007$**, eta squared = 0.147	Teachers with less experience: 5.64, 1.81 Teachers with more experience: 7.03, 1.53
Human grades**	$F = 8.617$, $p = 0.005$**, eta squared = 0.158	Teachers with less experience: 6.27, 1.59 Teachers with more experience: 7.49, 1.18
AI grades	$F = 1.435$, $p = 0.237$, eta squared = 0.30	Teachers with less experience: 6.5, 1.61 Teachers with more experience: 7.04, 1.46

**$p < 0.01$.
SD, standard deviation.

personality predispositions when trying to assess the originality of assignments, on the contrary, they were able to approach the task objectively. While the literature hints at a possible role of personality traits in the ability to recognize dishonest behavior and lies (e.g., extraversion and openness to experience predict accuracy in deception detection[57]), in the present study the Big Five traits did not appear associated with the identification of AI cheating.

Further analyses assessed teachers' self-efficacy in assessing assignments' originality and personality traits. While other studies have been published that involved education professionals in assessing school works written by AI,[58] to our knowledge such a psychological investigation is still unprecedented in the literature. Openness to experience and conscientiousness predicted teachers' self-efficacy in identifying the originality of assignments, even explaining a notable portion of the variance considering the relatively small sample size. While self-efficacy is generated by sources that are well-known in the literature (mastery, vicarious experiences, social persuasion, and transient physiological states[59]), personality traits can improve or reduce the accessibility of such sources. Consistently with our results, Openness to experience is often reported in the literature as strongly associated with both self-esteem and confidence in various contexts, but not overconfidence,[60–63] as open-to-experience individuals tend to have a positive attitude toward new challenges and their own ability to face them. Conscientiousness, as related to being ordered and thorough in one's activities, is also often associated with self-efficacy[64–67] and even with self-deception (i.e., tendency to have an unrealistically positive self-image).[68]

Conclusions

The aim of the research was to examine teachers' ability and self-efficacy in identifying whether assignments were written by human students or AI. The study highlights a potential "AI bias," wherein more experienced teachers correctly attributed AI-generated assignments to AI, but also mistakenly attributed student-generated assignments to AI. This suggests that professional expertise may play a significant role in shaping teachers' interactions with AI in educational settings. Additionally, personality traits such as conscientiousness and openness to experience appear to predict teachers' self-perceived ability to assess the originality of assignments. Teachers with more years of experience tended to award higher grades to student-written assignments, as opposed to AI-generated ones.

This study was not exempt from limitations. While to our knowledge, it is among the first studies to assess teachers' identification of students-/AI-made assignments, the responses used as experimental operators were relatively brief and simple compared with real-life full assignments. Secondarily, teachers in our sample were mostly female. Also, they were invited to assess anonymous assignments, not every day work from the students they know. Therefore, the results of this study may not be fully representative of teachers and of their assessment "in the wild." Moreover, the teachers in the sample had to evaluate the originality of assignments from different disciplines, not always consistent with their own specialties, and AI and students were given different topics for the assignments. While this was done to ensure a variety of our experimental stimuli, we cannot rule out that having to assess assignments related or unrelated to one's own expertise may lead to different results. It should also be said that students who would cheat may not just turn in AI-made assignments like those seen here but try to "collaborate" with the tool. That considered, future studies may use stimuli and variables such as those employed here, in order to assess their relationship with other characteristics of teachers, students, and specific educational contexts.

As a conclusion, an important aspect to underline is the need for teachers to identify the tasks that are entirely performed by AI. Indeed, if AI is used to complete a task without a genuine understanding of prompts, not only will it be evident that it was generated by AI, but also it will be incomplete, unoriginal, and imprecise. However, if the task is completed correctly, it will mean that the student has been able to guide AI effectively, resulting in a task where their role has been central. A constructive and interactive use by students is a skill required in the modern world that should not be hindered but rather supported didactically by teachers.

This study contributes to identifying factors that affect professionals' beliefs and attitudes toward AI in the delicate field of education, which is important to guide human-centered implementation of the technology. Successful implementation of AI in education does not depend on the effectiveness of the technology only, because professionals understand such a sophisticated tool can be used unfairly, altering if not compromising the fundamental aims of the educational effort. Since beliefs about one's ability to deal with a technology can be influenced by personality, implementation can consider individual differences when selecting professionals who would be responsible for introducing the technology in the context, maybe mentoring their colleagues. Indeed, selecting appropriate professionals to foster appropriate technology adoption has been regarded as one of the possible solutions to AI implementation issues within organizations.[69] On the contrary, to introduce any AI tool within an educational context (e.g., a school), it may be wise to adopt a user-centered design approach,[70,71] that is, the technology should be designed based on users' needs, expertise in their field, individual predispositions and preexisting attitudes. Hopefully, this would help to unify students' and teachers' aspirations, by developing AI tools capable of supporting desirable pedagogical processes.

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Authors' Contributions

M.C.C.: Conceptualized the study and wrote the first draft. A.C.: Edited the article and participated in data preparation and analysis. C.S. and L.S.: Participated in writing, edited the article, and performed data collection. S.T.: Participated in conceptualization, writing, and supervised the whole process.

Author Disclosure Statement

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Supplementary Materials

Supplementary Appendix

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