ARTIFICIAL INTELLIGENCE AND EMOTIONS: AN EXPLORATORY SURVEY ON THE PERCEPTION OF A.I. TECHNOLOGIES BETWEEN SUPPORT TEACHERS IN TRAINING

INTELLIGENZA ARTIFICIALE ED EMOZIONI: UN'INDAGINE ESPLORATIVA SULLA PERCEZIONE DELLE TECNOLOGIE A.I. TRA DEGLI INSEGNANTI DI SOSTEGNO IN FORMAZIONE

Guendalina Peconio[1]
Università degli Studi di Foggia
guendalina.peconio@unifg.it

Michele Ciletti[1]
Università degli Studi di Foggia
michele_ciletti.587188@unifg.it

Martina Rossi[1]
Università degli Studi di Foggia
martina.rossi@unifg.it

Giusi Antonia Toto[1]
Università degli Studi di Foggia
giusi.toto@unifg.it

Double Blind Peer Review

Citazione
Peconio, G., Ciletti, M., Rossi, M., & Toto, G.A. (2024). Artificial intelligence and emotions: an exploratory survey on the perception of AI technologies between support teachers in training, *Giornale Italiano di Educazione alla Salute, Sport e Didattica Inclusiva*, 8(2), Edizioni Universitarie Romane.

Doi:
https://doi.org/10.32043/gsd.v8i3.1117

gsdjournal.it
ISSN: 2532-3296
ISBN 978-88-7730-494-0

ABSTRACT
This paper proposes a reflection on Artificial Intelligence technologies used for affective computing by analyzing the point of view of support teachers in training at the University of Foggia. To achieve this, an exploratory survey was conducted on with 596 support teachers in training at the University of Foggia's TFA Support (F=81.9%) by submitting a questionnaire adapted from the Godspeed scales proposed by Bartneck et al. (2009) and a questionnaire developed by Heerink et al. (2019).

Il presente paper propone una riflessione sulle tecnologie di intelligenza artificiale utilizzate per l'affective computing analizzando il punto di vista di alcuni insegnanti di sostegno in formazione dell'Università di Foggia. A tal fine, è stata condotta un'indagine esplorativa su 596 insegnanti di sostegno in formazione presso il TFA dell'Università di Foggia (F=81,9%), sottoponendo un questionario adattato dalle scale Godspeed proposte da Bartneck et al. (2009) e da un questionario sviluppato da Heerink et al. (2019).

KEYWORDS
Artificial Intelligence, support teachers in training, trust, affective computing, anthropomorphism
Intelligenza Artificiale, insegnanti di sostegno in formazione, fiducia, affective computing, antropomorfismo

Received 30/04/2024
Accepted 14/06/2024
Published 24/06/2024

Introduction

Over the past few years, several changes have been enacted in the world of education and training; these changes, driven by the increasingly intensive use of Information and Communication Technologies (ICTs), have their roots in the 20th century, a century in which a new concept of culture, Digital Culture, was born, understood as the way in which the development of individual and social culture is shaped by the introduction and use of digital technologies (Weritz et al., 2020). At the heart of Digital Culture are digital technologies, which are able to shape more interconnected, collaborative and participatory forms of culture.

The advent of digital culture and new technologies have made it possible to integrate but more importantly support education through multiple remote resources. The goal is to ensure learning from a lifelong perspective, beyond the spatial-temporal limitations imposed by traditional educational systems (Garzón Artacho et al., 2020). All technologies have had the effect of enhancing and amplifying human capabilities. In particular, we can understand ICT as one of the most powerful "technologies of the mind" developed to date. They are directed to support and amplify fundamental capabilities of our cognitive and mental processes, such as remembering, communicating and learning knowledge, and processing and developing it.

Digital technologies, over time, have continued to evolve, leading to the development of Artificial Intelligence. According to the definition of Chen and colleagues (2020), AI can be understood as the ability of machines to adapt to new situations, deal with emergent situations, solve problems, answer questions, design devices, and perform various other functions that require a certain level of intelligence typically evident in humans; the goal, therefore, is to study the behaviour of intelligence in humans with an attempt to computerize that behaviour into a technological artifact.

The use of AI in education and training could revolutionize learning; in this regard, particular regard is paid to Affective Computing, an umbrella term aimed at human emotions, feelings, emotion recognition as well as sentiment analysis (Wang et al., 2022). Affective Computing, if used properly, could revolutionize what is the learning process as emotions, their recognition and management, play an essential

[1] For the purpose of scientific recognition, the introduction and the conclusion are to be attributed to Martina Rossi, paragraph 1 is to be attributed to Michele Ciletti, paragraph 2 is to be attributed to Guendalina Peconio and a revision of the overall paper is to be attributed to Giusi Antonia Toto.

role in several processes including decision making, problem solving, students' sense of self-efficacy and self-esteem (Marín-Morales et al., 2020). Moreover, students' emotions, if assessed quickly, could become a useful tool for developing interactive and highly personalized teaching resources (Salazar et al., 2021).

However, at present, this can only be made possible if teachers decide to adopt these techniques in their in their classrooms, and to do so, they would have to be sufficiently trained and informed about AI. and have a degree of confidence in these technologies. This applies not only to affective computing but also to any teaching strategy that uses AI.

In light of the above, Learning Science institute's research item, decided to conduct an exploratory research aimed at investigating the perceptions of teachers currently in training towards AI. Specifically, it was decided to investigate aspects related to their overall knowledge of the subject, their willingness to use such tools, the level of trust they perceive towards it, their psychological distance towards AI systems, and their perceptions towards anthropomorphising. To achieve this, an exploratory survey was conducted on with 596 support teachers in training at the University of Foggia's TFA Support (F=81.9%) by submitting a questionnaire adapted from the Godspeed scales proposed by Bartneck et al. (2009) and the questionnaire developed by Heerink et al. (2019), based on Venkatesh et al. (2003) Unified Theory of Acceptance and Use of Technology.

1. Large Language Models, Affective Computing and trust towards AI: a brief overview

In the last few years, and more specifically since November 2022, we have seen a major increase in public interest towards AI, and this interest is still steadily growing. While AI once was a topic strictly belonging to science fiction or to hopeful machine learning scientists, it has now become a part of everyday life for a considerable number of people. This is mainly attributable to the release of ChatGPT, an LLM chatbot (Large Language Model) which gained popularity after being made available and free for everyone by OpenAI (Wu et al., 2023). An LLM, during its initial training, is fed enormous amounts of labelled and curated textual data and learns the probability of certain words following others. After doing so - a complex process which requires large amounts of computational power and time - it is able to receive inputs from users in the form of natural language and to use algorithmic calculations based on matrices to stochastically determine a coherent output in response (Zhao et al., 2023). LLMs, though, lack explainability, in the

sense that the way they obtain the results we receive is still somewhat unclear (Zhao et al., 2024).

This revolutionary product is nothing more than the result of major breakthroughs in AI research that accelerated the development of new models at a scale never seen before. The first one concerns Deep Learning, a technique which exists since the '60s but that saw developments in the '00s that made it surpass each other AI technique (the so-called Deep Learning Revolution) (Deng & Yu, 2014). Deep Learning leverages many layers of non-linear information processing to extract increasingly higher-level features and concepts from an input (Deng & Yu, 2014). The excellent results produced in the 2010s brought a new interest - and funding - into the field. In 2017, Google's research team published the paper *Attention is all you need*, marking the start of a new era: *Transformers*, a new deep learning architecture, soon became the standard thanks to its never-seen-before ability to cut training times and costs (Vaswani et al., 2017). With the release of ChatGPT, many companies joined the race to AI and tried to replicate its success: the consequence is that now the average user has free (or affordable) access to a wide range of highly performing LLMs, focused on text, images and video, that can be used to produce content en masse in minimum amounts of time.

It goes without saying that such a revolution is requiring adjustments and adaptations in terms of society, working conditions, communication, education, ethics and many more fields.

Immediately intuitive applications such as researching information, copywriting and generating stock content are certainly not the only ones possible. Thanks to an ever-expanding API system, LLMs are starting to be integrated into all sorts of different services, and there is the potential to use them to support and even replace human agents working face-to-face with the public. As technology advances and becomes more reliable by scaling its training parameters - which has been shown to be effective, and we aren't seeing diminishing returns yet (Kaplan et al., 2020) - it becomes better at reasoning and at remembering long conversations, it hallucinates less, and generally behaves in a more human-like manner, while also developing emergent abilities not seen in smaller models (Wei et al., 2022): we could soon be at a point (and we may already be there) where it is complex for the general public to realize they are having an online conversation with an AI rather than a human. The impact is starting to be seen on social media and on the internet as a whole: bots fill timelines and comment sections, in the best case with the mere intent of generating interaction and ad revenue, in the worst to maliciously influence readers' opinions on political matters (Woolley, 2016).

Broadly speaking, a proliferation of unreliable information is currently observable, and, while this trend was already in action pre-2022, it is only getting worse now that it is easier than ever to mass-generate plausible news articles that have nothing factual inside them and share them on social media (Whyte, 2020). The overall tendency to use social media as a primary news source is exacerbating the problem, and fact-checking made directly by the end users is more required than ever.

Another factor to consider is AI's impact on the job market: many workers are being laid off and replaced by AI, mainly those whose tasks can be easily automated - call centre operators, copywriters, customer service workers. This may well simply be the necessary adjustment period of a technological revolution that will soon settle into a new normal, but it is undeniable that it is a possible cause of distrust and fear towards AI (Lane et al., 2023). Common narratives around the supposition that machine intelligence must be cold, rational and devoid of emotion and that creativity must be a peculiar trait of humans only is certainly contributing to the problem (Marrone et al., 2022): AI is slowly starting to replace creative work, not manual labour as often envisioned by science fiction (Hermann, 2023) - it writes poetry, draws paintings, shoots movies, and generally challenges our way of perceiving art and imagination.

Teaching is not exempt from the conversation. Well before the release and popularization of modern LLMs, the possibility of machines understanding and cataloguing human emotions was theorized by Picard (2000) in her book *Affective computing*. Since then, there have been numerous and promising efforts in developing algorithms capable of monitoring emotions in different ways. Facial recognition software analyses a user's face to detect expressions that could be associated with different emotional states - frowning can be linked to anger, for example. This is once again achieved thanks to machine learning, and specifically by training an algorithm with large datasets of labelled images displaying human emotions. The fully trained program, then, is able to gauge the similarities and differences between what it is seeing and what is in its training dataset, and outputs a value which shows how close it thinks the input is to its ideal representation of an emotion (Canal et al., 2022). Similar techniques can be used to analyse speech, body gestures and even written language (Syngh & Goel, 2022; Wu et al., 2022; Wankhade et al., 2022). It is also possible to obtain valuable insights through physiological monitoring (Saganowski et al., 2022).

One of the main applications of this technology is, precisely, teaching: because learning is affected by one's emotions (Tian et al., 2014), being able to determine

automatically and (theoretically) with mathematical precision a student's current mood is a valuable resource for a teacher. Because emotions change suddenly according to external factors (Li et al., 2022), live monitoring can be useful to understand how a student is reacting to a particular section of a lecture and tweak it accordingly. Moreover, as different students react differently to the same learning situations, recognizing what is well accepted and what isn't by a single student allows a teacher to develop personalized learning strategies and materials, in order to accommodate the specific needs of each student. All of this can obviously be done even without the aid of affective computing, but the hope is that this technology could save time and catch even small changes that would otherwise be missed even by a seasoned teacher, who couldn't possibly pay close enough attention to each single student.

In the last few years, there have been attempts to integrate affective computing technologies into classrooms. Studies such as those by Yadegaridehkordi and colleagues (2019) and by Wu and colleagues (2016) are a great resource to catch up on them. However, some considerable challenges were noticed: integrating multimodal information, understanding complex emotions beyond restrictive labels, capturing emotions efficiently in dynamic environments, developing efficient and rich enough databases (Wu et al., 2016).

Since the rise of generative LLMs, though, new frontiers have opened for affective computing research. Large Language Models, by design, express themselves through our natural language, attempting to establish a certain psychological proximity between themselves and their users (Alabed et al., 2022). Furthermore, they aren't limited by a single type of input, but are instead embracing multimodality, which allows them to understand and communicate through text, audio, video and even physiological signals (Wang et al., 2023). This is why, for example, LLM chatbots are starting to be integrated into medial fields, especially in regard to the delicate tasks of diagnosing, educating trainees and communicating efficiently with patients (Li et al., 2024; Ostherr, 2022). At the same time, a similar process is happening in education: AI systems are being used to design curricula and learning activities, provide feedback on students' homework, and even as intelligent tutoring systems (Lo, 2023; Limo et al., 2023). Paired with emotional recognition technologies, LLMs could partially solve the issues highlighted before and bring us closer to new realities of affective computing more accessible, efficient and easy to use than ever.

It is important, though, to remember that adopting AI into classrooms is not a simple task, and, as of today, falls mainly on the shoulders of resourceful teachers.

However, it is reasonable to assume that many others do not possess the necessary literacy in regards to AI to be able to use it effectively with their students, or simply do not want to do so because of their personal opinions - as said before, teaching is widely considered to be a job revolving around comprehension, empathy and emotions, something usually not associated with machines (García-Peñalvo, 2023).

Our research questions stem from this reality: are teachers ready to embrace AI? Do they want to do so? Do they feel like a machine could be useful in assessing their students' emotions, or do they consider it their own prerogative? To gain some insights, we investigated the feelings of a group of teachers in training at the University of Foggia.

2. The study

As has been pointed out, in the context of education, the integration of artificial intelligence (AI) technologies has revolutionary potential, especially in the field of learning. Affective computing, one of the emerging branches of AI, offers the possibility of rapidly assessing students' emotions, paving the way for the development of highly personalized and interactive teaching resources (Salazar et al., 2021). However, for these promising prospects to become reality, it is essential that teachers are willing to adopt these technologies into their teaching practices. This requires not only a thorough understanding of artificial intelligence, but also a degree of trust and acceptance of these new modes of teaching.

2.1 Aims and research questions

This exploratory study aims to investigate prospective teachers' feelings and perceptions toward artificial intelligence, focusing on their knowledge of the topic, willingness to use it, level of confidence, and perceived psychological distance to the investigated technology. In addition, we want to explore whether teachers tend to anthropomorphize artificial intelligence and what implications this finding may have with respect to their attitude toward adopting AI-based teaching strategies.

Through the analysis of data obtained from a questionnaire, this study aims to generate an informed discussion and open new perspectives for future research and interventions in the field of integrating artificial intelligence into the educational environment.

2.2 Participants and procedures

Participants for this study were selected from students enrolled in the TFA Support course at the University of Foggia in the 2022/2023 academic year. Data collection was done by completing a self-report questionnaire in Italian using the Google Forms platform.

At the conclusion of the procedure, the study group that completed the socio-demographic section consisted of n=327 teachers (82.3% female; 15.9% male; 1.5% preferred not to specify, 0.3% other) with a mean age of 40.4 years (standard deviation = 8.9). The majority of them (73.4%) work in secondary school (26% childhood; 0.6% secondary II).

Regarding teaching experience, 32.4 percent of the participants have prior experience as both curricular and support teachers, 26.6 percent only as curricular teachers and 19.3 percent only as support teachers; the remaining 21.7 percent of the sample have no teaching experience at school. In the latter case, to ensure uniformity in response, participants without experience were asked to consider internship activities while answering the questions.

All socio-demographic characteristics of the participants are shown in Table 1.

VARIABLES	N (%)
GENDER	
Donne	269 (82,3%)
Uomo	52 (15,9%)
Preferisco non specificarlo	5 (1,5%)
Altro	1 (0,3%)
TYPE OF COURSE ATTENDED	
Secondaria di I grado	240 (73,4%)
Infanzia	85 (26%)
Secondaria di II grado	2 (0,6%)
TEACHING EXPERIENCE	
Sì, sia come docente curriculare che di sostegno	106 (32,4%)
Sì, come docente curriculare	87 (26,6%)
Sì, come docente di sostegno	63 (19,3%)
No	71 (21,7%)

Table 1 – Participants' socio-demographic characteristics (n=327)

2.3 Materials and procedures

Data were sourced through a self-report questionnaire administered through the Google Forms platform. The questionnaire, in addition to a socio-demographic section, included three control, closed-ended questions designed to investigate whether the study participants had ever used AI tools, whether they had received specific training on AI, and whether they were aware of the possibilities of identifying emotions using AI software; the questions are available in Table 2.

Questions	Answers
Ha mai ricevuto formazione specifica su cosa sia l'Intelligenza Artificiale, come funzioni e/o come utilizzare strumenti fondati su di essa?	Sì, ho ricevuto formazione di questo tipo No, ma ritengo di avere una sufficiente conoscenza a riguardo grazie a ricerche personali No, e non ritengo di avere sufficiente conoscenza a riguardo
È a conoscenza della possibilità di identificare le emozioni tramite software di Intelligenza Artificiale? Se sì, si è mai trovat* ad usare strumenti di questo tipo?	Sì, ne sono a conoscenza e ho usato strumenti di questo tipo Sì, ne sono a conoscenza ma non ho mai usato strumenti di questo tipo No, non ne ero a conoscenza
Sa cos'è l'Affective Computing?	Sì No

Tabella 2 – Control questions

In addition to these control questions, the following measurement scales were used:

- Godspeed scale by Bartneck (2008) - Italian version by Bartneck (2023). This instrument used to assess users' responses to autonomous systems or agents, such as robots or computer interfaces. The Godspeed scale presents several dimensions that reflect user perceptions of interaction with the system. It consists of 5 subscales designed to investigate perceptions with respect to: anthropomorphism; animation; likability; perceived intelligence; and perceived safety.

- A questionnaire proposed by Heerink et al. (2009) based on the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003). The present questionnaire featured 36 items that investigated anxiety (ANX), attitude (ATT), facilitating conditions (FC), intention to use (ITU), perceived adaptability (PA), perceived enjoyment (PE), perceived sociability (PS), perceived usefulness (PU), social influence (SI), social presence (SP), and trust (TRU) of participants. In the present research, the questionnaire was adapted to the aforementioned perceptions with respect to the use of AI systems.

2.4 Results and discussion

The study conducted on support teachers in training used Bartneck's (2008) Godspeed Scale to assess perceptions of Artificial Intelligence (AI). The results revealed the following averages in the dimension of anthropomorphism: 2.8 (on a Likert scale from "false" to "natural"). As for the perception of consciousness, the mean was 2.75 (on a scale from "unconscious" to "conscious"). Finally, for the dimension of realism, the mean was 2.81 (on a scale from "artificial" to "realistic"). These results indicate that trainee teachers tend to perceive AI as relatively natural and realistic, but with less pronounced consciousness. Analysis of the results suggests several interesting considerations. The relatively high average in the anthropomorphism dimension indicates that support teachers in training tend to perceive AI as more human or natural. This could reflect an open-mindedness toward advanced technology and a propensity to conceive of AI as an integral part of the educational environment. However, the lower mean in perceived consciousness might indicate a limited perception of AI's ability to act consciously or autonomously. This could reflect concerns about AI's decision-making abilities and responsibility in interactions with students. Finally, the mean on the realism dimension suggests that teachers in training see AI as a technology that is fairly realistic, but not fully assimilated to human beings. This balance between perceived naturalness and artificiality of AI could influence teachers' expectations of its role and capabilities in the educational environment.

Support teachers in training manifest a generally positive attitude toward AI, as indicated by the animation dimension data. High averages in all sub-dimensions - living (3.03), animated (3.09), interactive (3.18), and engaging (3.13) - suggest that teachers tend to perceive AI as dynamic, animated, interactive, and engaging. This perception may promote the adoption and use of AI as an educational resource, seen as an active and participatory entity in the learning environment.

Results regarding liking also show positive acceptance of AI. The high averages on all dimensions - pleasantness (3.2), likeability (3.19), friendliness (3.24) and agreeableness (3.2) - indicate that teachers perceive AI favourably, attributing desirable and positive characteristics to it. This could promote a more harmonious and collaborative relationship between teachers and technology, facilitating greater integration in the school environment.

Regarding perceived intelligence, the results show a generally positive perception of AI by teachers. The high averages in all sub-dimensions - competence (3.2), education (3.16), responsibility (3.06), intelligence (3.15) and judgment (3.12) - indicate that teachers attribute some cognitive and decision-making ability to AI. However, the slightly lower averages compared to the previous dimensions may indicate a caution in attributing too much intelligence or competence to AI.

Finally, regarding perceived safety, the results show ambivalence toward AI. Although the averages are generally moderate - anxiety (3.06), agitation (2.73) and surprise (2.77) - any concerns about AI's safety and stability in the educational environment may need to be addressed. The overall results (shown in Table 3) suggest a predominantly positive attitude of support teachers in training toward AI, with a favourable perception of its animate, sympathetic, intelligent, and interactive characteristics.

Item	Range (1-5)	Mean (SD)
ANTROPOMORFISMO	Falso-naturale	2,8 (0,81)
ANTROPOMORFISMO	Incosciente-cosciente	2,75 (0,83)
ANTROPOMORFISMO	Artificiale-realistico	2,81 (0,89)
ANIMAZIONE	Morto-vivente	3,03 (0,88)
ANIMAZIONE	Inanimato-animato	3,09 (0,93)
ANIMAZIONE	Inerte-interattivo	3,18 (0,96)
ANIMAZIONE	Apatico-partecipativo	3,13 (0,95)
SIMPATIA	Spiacevole-piacevole	3,2 (0,95)
SIMPATIA	Antipatico-simpatico	3,19 (0,91)
SIMPATIA	Ostile-amichevole	3,24 (0,91)
SIMPATIA	Sgradevole-gradevole	3,2 (0,93)
INTELLIGENZA PERCEPITA	Incompetente-competente	3,2 (0,84)
INTELLIGENZA PERCEPITA	Ignorante-istruito	3,16 (0,84)

INTELLIGENZA PERCEPITA	Irresponsabile-responsabile	3,06 (0,85)
INTELLIGENZA PERCEPITA	Poco intelligente-intelligente	3,15 (0,85)
INTELLIGENZA PERCEPITA	Insensato-giudizioso	3,12 (0,83)
SICUREZZA PERCEPITA	Ansioso-rilassato	3,06 (0,87)
SICUREZZA PERCEPITA	Calmo-agitato	2,73 (0,84)
SICUREZZA PERCEPITA	Sereno-sorpreso	2,77 (0,82)

Table 3 – Results related to the Godspeed scale adapted to Artificial Intelligence

The analysis of data obtained from the adaptation of the questionnaire proposed by Heerink et al. (2009) based on the Unified Theory of Acceptance and Use of Technology (UTAUT) provides a detailed view of the perceptions of trainee support teachers toward Artificial Intelligence (AI). Initially, it is interesting to note that the intention to use AI (ITU) has a relatively high average of 3.2 out of 5. This suggests a positive predisposition of support teachers toward the use of AI in their instructional practices. However, this finding needs to be contextualized by considering the other variables. The perceived usefulness (PU) of AI has a mean of 3.18, indicating that support teachers in training see AI as a useful tool to improve the teaching and learning process. This is an encouraging result, as AI is seen as an opportunity to optimize the educational experience.

However, it should be noted that participants' confidence (TRU) in AI has a lower average of 2.37. This suggests some uncertainty or lack of confidence of support teachers in fully relying on AI. It is possible that there are concerns about the accuracy or reliability of AI systems in the educational environment. Facilitating conditions (FC), with a mean of 2.5, also indicate that support teachers may perceive obstacles or difficulties in using AI, such as lack of access to tools or resources needed to effectively integrate technology into their teaching practices.

In addition, the analysis shows that social presence (SP) and perceived sociability (PS) of AI have relatively low averages, 2.66 and 2.71, respectively. This could indicate limited perceptions of support teachers regarding AI's ability to provide a meaningful social or human interaction experience in the educational environment.

Finally, it should be noted that anxiety (ANX) and perceived enjoyment (PE) have moderate averages, 2.95 and 2.84, respectively. These results suggest that support teachers may experience some level of anxiety or concern about using AI, while they may not perceive the experience with AI as particularly fun or fulfilling.

In conclusion, the data analysis indicates a positive predisposition of support teachers toward the use of AI in the educational environment, but also a number of concerns and challenges that need to be addressed, such as confidence toward the technology, facilitating conditions for its use, and perceptions of its presence and sociability.

Item	Range (1-5)	Mean (SD)
ANX – Ansia	Del tutto in disaccordo - del tutto in accordo	2,95 (1,04)
ATT - Atteggiamento	Del tutto in disaccordo - del tutto in accordo	3,08 (0,94)
FC – Condizioni Facilitanti	Del tutto in disaccordo - del tutto in accordo	2,5 (0,95)
ITU – Intenzione di usare	Del tutto in disaccordo - del tutto in accordo	3,2 (0,94)
PA – Adattabilità percepita	Del tutto in disaccordo - del tutto in accordo	3,15 (0,19)
PE – Divertimento percepito	Del tutto in disaccordo - del tutto in accordo	2,84 (0,95)
PS – Socievolezza percepita	Del tutto in disaccordo - del tutto in accordo	2,71 (0,95)
PU – Utilità percepita	Del tutto in disaccordo - del tutto in accordo	3,18 (0,9)
SI – Influenza sociale	Del tutto in disaccordo - del tutto in accordo	2,94 (0,87)
SP – Presenza sociale	Del tutto in disaccordo - del tutto in accordo	2,66 (1,16)
TRU – Fiducia dei partecipanti	Del tutto in disaccordo - del tutto in accordo	2,37 (0,97)

Table 4 – Results of the scale proposed by Heerink et al. (2009) adapted to artificial intelligence

Conclusions

In light of what has been highlighted in this exploratory research, there is no doubt that the use of AI applications in teaching practices, with a focus on the use of Affective Computing, presents interesting prospects but equally significant challenges for teachers.

The integration of tools based on Affective Computing can offer real opportunities to enhance the learning experience of students by enabling personalization of teaching to their emotional and, consequently, cognitive needs.

The data collected and analysed emphasize that support teachers in training manifest a generally positive attitude toward AI, perceiving it as dynamic, interactive, engaging, and enjoyable to use. They also have a tendency to view AI as natural and realistic, even from an anthropomorphic perspective, thus suggesting an openness toward such technology and a view of AI as a possible tool to be integrated into the educational environment.

Although, however, the sample views AI as natural and realistic, on the other hand, they state that it does not seem to be a technology that is completely assimilated with human beings. This contradiction between perceived naturalness and artificiality of AI could negatively influence teachers' expectations of its use and integration into the learning process.

Although there is a positive predisposition for the use of AI by teachers, there are equal challenges and concerns including frustration in having to use and cope with new tools and technological advances without having the means to learn how to exploit their potential. These findings offer useful insights for developing implementation approaches and specific training programs aimed at fostering effective and successful integration of AI in inclusive education. It is essential, therefore, to responsibly address the challenges associated with this technology, and, at the same time, to ensure adequate training for teachers to enable them to take full advantage of the potential of these technologies to enhance the learning experience of students and support teachers in their pedagogical practice.

References

Alabed, A., Javornik, A., & Gregory-Smith, D. (2022). AI anthropomorphism and its effect on users' self-congruence and self–AI integration: A theoretical framework and research agenda. Technological Forecasting and Social Change, 182, 121786.

Bartneck, C., Croft, E., Kulic, D. & Zoghbi, S. (2009). Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. International Journal of Social Robotics, 1(1) 71-81.

Bartneck, C. (2023). Godspeed questionnaire series: Translations and usage. In International Handbook of Behavioral Health Assessment (pp. 1-35). Cham: Springer International Publishing.

Canal, F. Z., Müller, T. R., Matias, J. C., Scotton, G. G., de Sa Junior, A. R., Pozzebon, E., & Sobieranski, A. C. (2022). A survey on facial emotion recognition techniques: A state-of-the-art literature review. Information Sciences, 582, 593-617.

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. Ieee Access, 8, 75264-75278.

Deng, L., & Yu, D. (2014). Deep learning: methods and applications. Foundations and trends® in signal processing, 7(3–4), 197-387.

García-Peñalvo, F. J. (2023). The perception of Artificial Intelligence in educational contexts after the launch of ChatGPT: Disruption or Panic?.

Garzón Artacho, E., Martínez, T. S., Ortega Martin, J. L., Marin Marin, J. A., & Gomez Garcia, G. (2020). Teacher training in lifelong learning—The importance of digital competence in the encouragement of teaching innovation. Sustainability, 12(7), 2852.

Heerink, M., Kröse, B., Evers, V., and Wielinga, B. (2009). Measuring acceptance of an assistive social robot: A suggested toolkit, in Proceedings of the RO-MAN 2009 The 18th IEEE International Symposium on Robot and Human Interactive Communication, (Toyama: IEEE), 528–533.

Hermann, I. (2023). Artificial intelligence in fiction: between narratives and metaphors. AI & society, 38(1), 319-329.

Kaplan, J., McCandlish, S., Henighan, T., Brown, T.B., Chess, B., Child, R., Gray, S., Radford, A., Wu, J., & Amodei, D. (2020). Scaling Laws for Neural Language Models. ArXiv, abs/2001.08361.

Lane, M., Williams, M., & Broecke, S. (2023). The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers.

Li, J., Dada, A., Puladi, B., Kleesiek, J., & Egger, J. (2024). ChatGPT in healthcare: a taxonomy and systematic review. Computer Methods and Programs in Biomedicine, 108013.

Li, Y., Wei, J., Liu, Y., Kauttonen, J., & Zhao, G. (2022). Deep learning for micro-expression recognition: A survey. IEEE Transactions on Affective Computing, 13(4), 2028-2046.

Limo, F. A. F., Tiza, D. R. H., Roque, M. M., Herrera, E. E., Murillo, J. P. M., Huallpa, J. J., ... & Gonzáles, J. L. A. (2023). Personalized tutoring: ChatGPT as a virtual tutor for personalized learning experiences. Przestrzeń Społeczna (Social Space), 23(1), 293-312.

Lo, C. K. (2023). What is the impact of ChatGPT on education? A rapid review of the literature. Education Sciences, 13(4), 410.

Marín-Morales, J., Llinares, C., Guixeres, J., & Alcañiz, M. (2020). Emotion recognition in immersive virtual reality: From statistics to affective computing. Sensors, 20(18), 5163.

Marrone, R., Taddeo, V., & Hill, G. (2022). Creativity and artificial intelligence—A student perspective. Journal of Intelligence, 10(3), 65.

Ostherr, K. (2022). Artificial intelligence and medical humanities. Journal of Medical Humanities, 43(2), 211-232.

Picard, R. W. (2000). Affective computing. MIT press.

Saganowski, S., Perz, B., Polak, A., & Kazienko, P. (2022). Emotion recognition for everyday life using physiological signals from wearables: A systematic literature review. IEEE Transactions on Affective Computing.

Salazar, C., Aguilar, J., Monsalve-Pulido, J., & Montoya, E. (2021). Affective recommender systems in the educational field. A systematic literature review. Computer Science Review, 40, 100377.

Singh, Y. B., & Goel, S. (2022). A systematic literature review of speech emotion recognition approaches. Neurocomputing, 492, 245-263.

Tian, F., Gao, P., Li, L., Zhang, W., Liang, H., Qian, Y. et al (2014). Recognizing and regulating e-learners' emotions based on interactive Chinese texts in e-learning systems.Knowledge-Based Systems,55, 148–164.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. Advances in neural information processing systems, 30.

Venkatesh, V., Morris, M., Davis, G., and Davis, F. (2003). User acceptance of information technology: toward a unified view. MIS Q. 27, 425–478.

Wang, D. Q., Feng, L. Y., Ye, J. G., Zou, J. G., & Zheng, Y. F. (2023). Accelerating the integration of ChatGPT and other large-scale AI models into biomedical research and healthcare. MedComm–Future Medicine, 2(2), e43.

Wang, Y., Song, W., Tao, W., Liotta, A., Yang, D., Li, X., ... & Zhang, W. (2022). A systematic review on affective computing: Emotion models, databases, and recent advances. Information Fusion, 83, 19-52.

Wankhade, M., Rao, A. C. S., & Kulkarni, C. (2022). A survey on sentiment analysis methods, applications, and challenges. Artificial Intelligence Review, 55(7), 5731-5780.

Wei, J., Tay, Y., Bommasani, R., Raffel, C., Zoph, B., Borgeaud, S., ... & Fedus, W. (2022). Emergent abilities of large language models. arXiv preprint arXiv:2206.07682.

Weritz, P., Braojos, J., & Matute, J. (2020). Exploring the antecedents of digital transformation: Dynamic capabilities and digital culture aspects to achieve digital maturity.

Whyte, C. (2020). Deepfake news: AI-enabled disinformation as a multi-level public policy challenge. Journal of cyber policy, 5(2), 199-217.

Woolley, S. C. (2016). Automating power: Social bot interference in global politics. First Monday.

Wu, C. H., Huang, Y. M., & Hwang, J. P. (2016). Review of affective computing in education/learning: Trends and challenges. British Journal of Educational Technology, 47(6), 1304-1323.

Wu, J., Zhang, Y., Sun, S., Li, Q., & Zhao, X. (2022). Generalized zero-shot emotion recognition from body gestures. Applied Intelligence, 1-19.

Wu, T., He, S., Liu, J., Sun, S., Liu, K., Han, Q. L., & Tang, Y. (2023). A brief overview of ChatGPT: The history, status quo and potential future development. IEEE/CAA Journal of Automatica Sinica, 10(5), 1122-1136.

Yadegaridehkordi, E., Noor, N. F. B. M., Ayub, M. N. B., Affal, H. B., & Hussin, N. B. (2019). Affective computing in education: A systematic review and future research. Computers & Education, 142, 103649.

Zhao, H., Chen, H., Yang, F., Liu, N., Deng, H., Cai, H., ... & Du, M. (2024). Explainability for large language models: A survey. ACM Transactions on Intelligent Systems and Technology, 15(2), 1-38.

Zhao, W., Zhou, K., Li, J., Tang, T., Wang, X., Hou, Y., Min, Y., Zhang, B., Zhang, J., Dong, Z., Du, Y., Yang, C., Chen, Y., Chen, Z., Jiang, J., Ren, R., Li, Y., Tang, X., Liu, Z., Liu, P., Nie, J., & Wen, J. (2023). A Survey of Large Language Models. ArXiv, abs/2303.18223.