



Exploration of ChatGPT adoption among Italian university students: an application of the technology acceptance model

Rossella Caliciuri¹ · Martina Milani¹ · Angela Sorgente¹ · Rosario Rodriguez¹ · Margherita Lanz¹

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Abstract

The rapid advancement of Artificial Intelligence technologies, particularly generative Artificial Intelligence, has revolutionized numerous domains, including education. This study investigates the adoption of ChatGPT, a prominent generative Artificial Intelligence tool, among 409 Italian university students (Mage=23.24 years, SD=2.61; 58.3% female) using the Technology Acceptance Model as a theoretical framework. A path analysis model was employed to examine the relationships between Technology Acceptance Model variables influencing ChatGPT's adoption. Findings suggest that perceived usefulness is the most influential factor, strongly affecting students' attitudes toward ChatGPT and their intentions to use it, and indirectly influencing its actual use. Perceived usefulness of ChatGPT is higher in students who have positive social norms related to technology use and perceive ChatGPT as easy to use, which, in turn, is predicted by a high level of technology self-efficacy and low level of technology anxiety. The results provide insights for academic institutions on how to facilitate the adoption of ChatGPT, contributing to more inclusive and effective education. Enhancing technology self-efficacy, promoting positive social norms related to technology use, and reducing technology anxiety are crucial for facilitating ChatGPT's integration into academic settings.

Keywords ChatGPT · Technology acceptance model · TAM · University students

Introduction

Today the world is confronting the widespread availability of Artificial Intelligence (AI). AI has been defined as “a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation” (Kaplan & Haenlein, 2019, p. 17). In recent years, the evolution of AI has undergone significant acceleration, largely due to advances in deep learning. Deep learning, which is based on neural networks with numerous layers, has enabled remarkable results in various fields of AI, thanks to its ability to learn from large amounts of data (Feuerriegel et al., 2024). This approach has led to the development of foundational models, which are at the core of many recent innovations, including the revolutionary field of generative AI. While

traditional AI applications focused on specific tasks such as image recognition or natural language processing, generative AI has elevated the capabilities of these technologies to a higher level (Feuerriegel et al., 2024). Generative models, powered by advanced deep learning architectures, are capable of autonomously creating new content, generating text, music, code, images, and even consolidating data from different sources (Dasborough, 2023).

One of the most prominent examples of generative AI is ChatGPT, a conversational chatbot that greatly enhances chatbot functionalities by incorporating deep learning and language models built on the Generative Pre-training Transformer (GPT) architecture (Radford et al., 2018). Specifically, trained on extensive online textual data, ChatGPT acquires an understanding of natural language structure, enabling it to generate coherent and intelligible text while also being capable of responding to various forms of input, including questions, statements, and requests for information spanning a wide spectrum of subjects (Graf & Bernardi, 2023; Kasneci et al., 2023; Khan et al., 2023). ChatGPT, in a short space of time, has garnered significant attention for its numerous applications (Macdonald et al., 2023). Bahrini

✉ Rossella Caliciuri
rossella.caliciuri@unicatt.it

¹ Department of Psychology, Università Cattolica del Sacro Cuore, Milan, Italy

et al. (2023) highlight significant applications across ten key domains: business and industry, education, science and technology, government and politics, healthcare and medicine, infrastructure, environment and sustainability, communication, arts and culture, lifestyle, and leisure. Among these, the education sector has been emphasized for its importance. ChatGPT plays a crucial role in education due to its versatility in supporting learning, research, teaching, and writing. Notably, it fosters inclusivity by offering personalized learning experiences, diverse content, and language support. Additionally, it assists in academic research by suggesting methodologies, aiding in analysis, and summarizing findings, while also supporting the creation of instructional content, engaging presentations, and dynamic discussions. Moreover, it enhances writing skills by providing feedback on grammar, vocabulary, and structure (Bahrini et al., 2023).

Several researchers, including Atadika et al. (2024), Fabio et al. (2024), Macdonald et al. (2023) and Wu et al. (2025), highlight the transformative potential of ChatGPT in academic settings. Delello et al. (2023) listed a series of ChatGPT advantages reported by college students themselves: ChatGPT streamlines writing processes, saves educators time, and supports students continuously. It promotes dynamic teaching methods, encourages real-world applications, enhances research and writing capabilities, and aids in project creation. However, the same study also highlights risks associated with ChatGPT. Students may exploit it to cheat, or rely too heavily on it, leading to limited critical thinking, or reduced human interaction. Privacy and cybersecurity concerns also arise from increased use of computer programs. Additionally, Lo (2023) raises issues regarding the generation of fake information and circumvention of plagiarism detectors.

Despite its potential, the misuse of ChatGPT poses risks and both educators and learners are called to use it responsibly. As researchers we are invited to expand the debate in the scientific community about generative AI, including ChatGPT (Van Dis et al., 2023). Within this framework, the current study aims to explore the adoption of ChatGPT among Italian university students through the Technology Acceptance Model (TAM, Davis, 1989).

Technology acceptance model (TAM)

The Technology Acceptance Model (TAM), introduced in 1985 by Fred Davis and grounded in the psychological theories of Planned Behavior by Ajzen and Fishbein (1980) and of Reasoned Action by Ajzen (1985), is the predominant framework for studying the factors influencing users' acceptance of technology. TAM has undergone several developments and extensions, both by Davis himself and other authors (Marangunić & Granic, 2015). In the version

of the model proposed in 1989, the TAM postulates that technology use is determined by behavioral intention (BI), considered to be jointly determined by perceived usefulness (PU) – that reflects the extent to which a person believes using the system would enhance their performance – and the individual's attitude towards system use (A) (Davis et al., 1989). The latter (A) is jointly determined by PU and perceived ease of use (PEOU) – that concerns the extent to which they believe using the system would require minimal effort (Davis et al., 1989). PU and PEOU thus represent the two core beliefs of TAM, shaping users' perceptions of technology's value and effort. Furthermore, it is posited that PEOU has a direct effect on PU; therefore, while PEOU is determined by external variables, PU is jointly determined by external variables and PEOU (Davis et al., 1989).

Despite the various adjustments made to this model over time and by the authors, the framework underlying it can be defined as a model consisting of three main elements which are interconnected as follows: (1) some external stimulus influence (2) the user's motivation to (3) use a particular technological system (see Fig. 1).

Although external variables significantly impact TAM, not all research models incorporate them (Li et al., 2008). According to Castiblanco Jimenez et al. (2020), commonly utilized external variables in studies where technology was applied for learning purposes include technology self-efficacy (SE), social norms related to technology use (SN), and technology anxiety (AX). Finally, TAM models may or may not incorporate certain control variables (e.g., gender, previous experience, age, etc.). According to Venkatesh and Davis (2000) control variables are crucial for enhancing a model's predictive accuracy; they demonstrated that out of eight tested models, six showed improved predictive power when additional relevant control variables were included.

Studies on students' adoption of ChatGPT via TAM as theoretical framework

In the last two years, since the advent of ChatGPT, several researchers have questioned the adoption of ChatGPT as a technology in educational and learning contexts by students. Some of them, in order to do so, have used the TAM as a theoretical framework. Consistent with the variations in TAM models previously discussed, empirical research on ChatGPT likewise employs different adaptations of the framework, as summarized in Table 1. For example, Duong et al. (2023), in a sample of higher education students, proposed a model in which perceived usefulness (PU) and perceived ease of use (PEOU) directly influence behavioral intentions (BI), and the academic use of ChatGPT (AU). Their model excludes attitude (A) toward using ChatGPT (as per the second model proposed by Davis in 1989) and

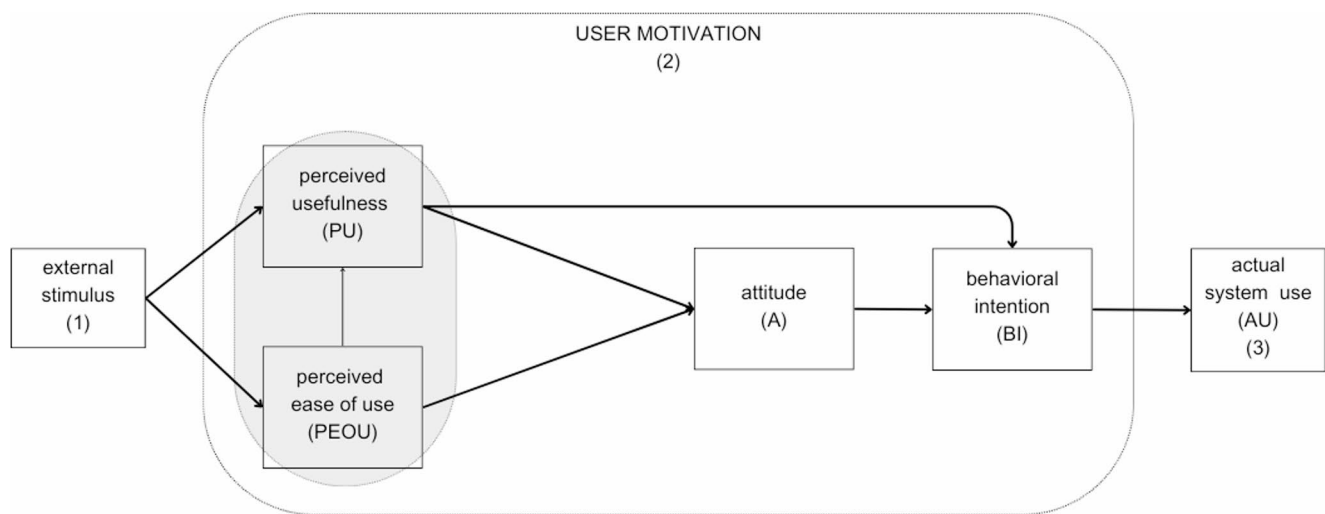


Fig. 1 Technology Acceptance Model by Davis, 1989

Table 1 Summary of Empirical Studies on Students' Adoption of ChatGPT via TAM

Reference	Study Design	Tam's Variables	Item	Data Analysis	Sample
Albayati, 2024	Cross-sectional	Core: PEOU, PU, A, BI. External: Privacy, Security, Social influence.	Rated on a 5-point Likert scale; based on the studies of Al-Emran et al. (2020); Cheung and Lee (2001); Davis et al. (1989); Gefen et al. (2003); Vankatesh & Davis (2000).	Structural Equation Modeling.	<i>N</i> =603 undergraduates in the United States of America.
Duong et al., 2023	Cross-sectional	Core: PEOU, PU, BI, AU Moderator: Knowledge Sharing.	Rated on a 5-point Likert scale; based on the studies of Al-Azawei and Alowayr (2020) and Al-Emran et al. (2020).	Multiple linear regression analysis with demographic controls to investigate the predicted relationships; PROCESS for mediation and moderation.	<i>N</i> =1389 students from 11 Vietnamese universities.
Liu & Ma, 2024	Cross-sectional	Core: PEOU, PU, A, BI, AU.	Rated on a 6-point Likert scale; based on the studies of Davis (1989); Bailey et al. (2022); Sun and Mei (2022).	Structural Equation Modeling.	<i>N</i> =405 Chinese EFL users.

any external variable, but introduces knowledge sharing as a moderator between BI and AU. Additionally, PU and BI are tested as mediators. Importantly, they do not label the two core beliefs as PU and PEOU: they rename them Performance Expectancy and Effort Expectancy, respectively, and define them equivalently to PU and PEOU. For clarity and consistency, in this paper we will refer to these two constructs as PU and PEOU. Instead, Liu and Ma (2024), in a sample of Chinese learners of English as a foreign language, using the first model outlined by Davis in (1989), include attitude toward using ChatGPT (A) as a variable that directly influences the academic use of ChatGPT (AU) but insert PU as a mediator between PEOU and A.

Similarly, Albayati (2024), in a sample of undergraduate students, utilizes the same theoretical model of Liu and Ma (2024) but incorporates four external variables: privacy, security, social influence, and trust.

As detailed in Table 1, the three studies differ in several important respects. First, although all of them adopt the TAM as a theoretical framework, they rely on different versions of the model: Duong et al. (2023) exclude attitude (A) and external variables while introducing knowledge sharing as a moderator; Liu and Ma (2024) employ Davis's (1989) model with attitude and mediation paths; and Albayati (2024) further extends it by adding four external constructs (privacy, security, social influence, and trust). Second, the

measurement of items is based on different prior sources, ranging from classic TAM studies (e.g., Davis, 1985, 1989) to more recent adaptations (e.g., Bailey et al., 2022; Sun & Mei, 2022). Third, the samples vary in both size and nationality: undergraduates in the United States (Albayati, 2024), higher education students in Vietnam (Duong et al., 2023), and Chinese EFL learners (Liu & Ma, 2024). Finally, the data analysis strategies vary: whereas two studies employ Structural Equation Modeling (SEM), one relies on multiple linear regression techniques.

To provide a clearer overview of the similarities and differences across the three studies, we produced a visual summary that integrates the core relationships of the TAM model tested by Albayati (2024), Duong et al. (2023), and Liu and Ma (2024). As illustrated in Fig. 2, the model focuses exclusively on the main constructs of TAM (PEOU, PU, A, BI, AU) and the paths among them, allowing a direct comparison of which relationships were examined and found significant across the three studies. The figure also reports the estimated coefficients and their significance levels, making it possible to evaluate the empirical support obtained in the different contexts.

In sum, the studies which adopted the TAM framework to study the academic use of ChatGPT among students are limited in number and use different TAM models. As understanding the acceptance and utilization of ChatGPT among university students holds significant interest, we stress the need for further research into the acceptance and influence of ChatGPT within educational settings, both to provide additional evidence on the relationships already tested and to explore further factors - such as technology self-efficacy, social norms related to technology use and technology anxiety - that could offer a deeper explanation of ChatGPT usage.

The present study

Utilizing the Technology Acceptance Model (Davis, 1989) as the theoretical framework, this study aims to investigate the adoption of ChatGPT among university students, a critical population for investigating the adoption of generative AI tools, such as ChatGPT, in educational settings. As highlighted by Van Dis et al. (2023), these tools are expected to significantly reshape scientific research, academic workflows, and knowledge production, making it essential to examine their uptake among those who are both current learners and future professionals. Furthermore, students in higher education are often among the first to engage with emerging educational technologies and are therefore considered early adopters (Venkatesh & Davis, 2000). Their behaviours and attitudes offer crucial insights into how new tools like generative AI may reshape academic practices and institutional norms (Van Dis et al., 2023). During the period when the data was collected (May 2023), ChatGPT was not widely known and used in Italy. For this reason, we decided to use “ChatGPT knowledge” as a control variable. Furthermore, relying on previous studies (Aburbeian et al., 2022; Guner & Acarturk, 2020; Ni & Cheung, 2023), we also used the following three technology-related external variables: technology self-efficacy (SE), social norms related to technology use (SN), and technology anxiety (AX).

This study contributes to the development of technology acceptance theory in four key ways. First, our study positions itself in relation to prior TAM research on ChatGPT, which has so far adopted heterogeneous configurations (Albayati, 2024; Duong et al., 2023; Liu & Ma, 2024). In contrast, our study advances this literature by modeling the complete TAM chain from beliefs to actual use. Second, we incorporate “ChatGPT knowledge” as a control variable, since at the time of data collection (May 2023) the tool had

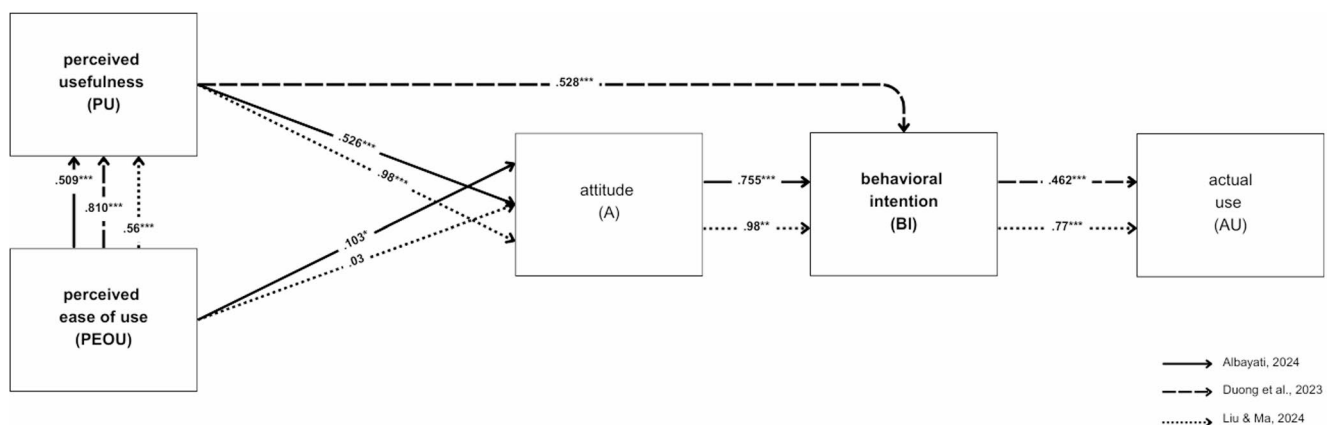


Fig. 2 Visual summary of the core TAM relationships (PEOU, PU, A, BI, AU) tested in Albayati (2024), Duong et al. (2023), and Liu and Ma (2024).

^aNote. The figure reports only the main constructs of the model, excluding external variables and moderators, and shows the path

coefficients and significance levels as presented in the original studies (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). Variables in bold are those included in all three studies, whereas the other two (A and AU) appear only in some of the models

only recently entered the Italian higher education landscape and students' familiarity with it remained limited. Controlling for prior knowledge allows us to distinguish users' structural beliefs about the technology (i.e., PU, PEOU) from the influence of mere exposure or familiarity, thus enhancing the internal validity of our model. Third, building on validated extensions of TAM in educational contexts, we introduce three theoretically grounded external variables: technology self-efficacy, social norms, and technology anxiety. These constructs are expected to account for additional variance in perceived ease of use, perceived usefulness, and behavioral intention, and may help differentiate the antecedents of TAM's two core beliefs. None of the previous studies on ChatGPT adoption have examined this differentiated pathway, thereby contributing a novel perspective on the psychological and social drivers of generative AI acceptance in higher education. **FOURTH, WE PRESENT ONE OF THE FIRST STUDIES CONDUCTED IN ITALY ON CHATGPT ADOPTION, CARRIED OUT DURING THE VERY EARLY STAGES OF GENERATIVE AI DIFFUSION. THIS UNIQUE TIMING MAKES IT POSSIBLE TO CAPTURE HOW STUDENTS' BELIEFS AND INTENTIONS TOWARD GENERATIVE AI DEVELOPED, WHILE ALSO HIGHLIGHTING THE FACTORS THAT PROMOTE ITS USE, SUCH AS PERCEIVED USEFULNESS, PERCEIVED EASE OF USE, TECHNOLOGY SELF-EFFICACY, SOCIAL NORMS RELATED TO TECHNOLOGY USE, AND TECHNOLOGY ANXIETY.**

Beyond these specific contributions, our study also strengthens the external validity of TAM. By extending the model with external variables not considered in prior ChatGPT studies and by testing it in a new population—Italian university students—we enhance both the explanatory power and the generalizability of the model. Taken together, the attention to internal validity (through the control of prior ChatGPT knowledge) and external validity (through new constructs and a new population) refines and extends TAM for the study of emerging, rapidly evolving AI technologies in education, while also offering evidence-based insights to inform policy, instructional design, and institutional decision-making.

Hypotheses

Based on previous studies that have tested the same TAM model (Aburbeian et al., 2022; Guner & Acarturk, 2020; Jatmikowati et al., 2021; Ni & Cheung, 2023; Roy et al., 2022), through path analysis, we aim to test the following hypotheses in the context of ChatGPT academic use (see Fig. 2).

Regarding external variables (1), we hypothesize that these influence perceptions about ChatGPT, specifically:

- SE influences PU (H1.1a) and PEOU (H1.1b).
- SN influences PU (H1.2a) and PEOU (H1.2b).
- AX influences PU (H1.3a) and PEOU (H1.3b).

Regarding the section related to user motivation (2), we hypothesize that:

- PEOU influences PU (H2.1a) and A (H2.1b).
- PU influences A (H2.2a) and BI (H2.2b).
- A influences BI (H2.3).
- BI influences AU (H2.4).

Additionally, the indirect effects of each variable will also be estimated.

Methods

Participants

Data was collected from May to July 2023. The convenient sample was composed of 409 university students in Italy aged 19–36 years ($M=23.24$; $SD=2.61$), mainly women (58.3%). The majority of participants report having at least heard of AI (91.4%) or ChatGPT (93.2%).

Procedure

The study protocol was approved by the Ethical Committee of the Department of Psychology of Università Cattolica del Sacro Cuore of Milan. The study consisted of a survey administered online. Data were collected through an online survey, and participation was entirely voluntary. The sample size was set a priori for model stability and statistical power. Testing the TAM via path analysis requires estimating at least 10 parameters, including six regression paths and four residual variances for the core TAM variables. In addition, our extended model incorporates three regression paths and three correlations for the external variables (SE, AX, SN), leading to a total of 16 estimated parameters. Following Jackson's (2003) rule of thumb of approximately 20 cases per estimated parameter, the minimum sample size required would be about 320 participants. By targeting around 400 participants, we ensured a conservative margin to achieve stable and adequately powered path estimates. Recruitment took place in May 2023 using a combination of snowball sampling and the Prolific platform. Participants recruited via snowball sampling, through university mailing lists and peer diffusion, did not receive any compensation. Specifically, email invitations were sent to university students aged 18 years or older who were enrolled at Italian universities, and recipients were encouraged to forward the invitation to their peers. Because this approach proved insufficient to reach the a priori sample size (i.e., 400 participants) within the required timeframe, recruitment was complemented with Prolific, where participants were compensated

in line with the platform's guidelines. This two-step strategy ensured both adequate statistical power and timely data collection, which was crucial for capturing early adoption. Individuals who agreed to take part in the study received online informed consent in accordance with the Declaration of Helsinki and, if the consent form was signed, participants were given access to the survey. The online survey was administered through Qualtrics and took approximately 20 min to complete.

Instruments

Besides providing socio-demographic data, participants were asked to complete different questionnaires. For each scale, we conducted Confirmatory Factor Analysis (CFA) and saved the factor scores. The variables of TAM were assessed by adapting the items used in the study by Huang et al. (2022) to the context of ChatGPT academic use. Specifically, the *perceived usefulness of ChatGPT use* (PU) was evaluated through three items (e.g., "Using ChatGPT would improve my academic performance"), rated on a Likert scale from 1 ("strongly disagree") to 5 ("strongly agree"). The mono-factorial structure of the PU was tested with a CFA and the saturated model reported high ($>.50$) and significant ($p <.001$) factor loadings. Internal consistency score was excellent (McDonald's $\omega = .907$). The *perceived ease of ChatGPT use* (PEOU) was evaluated through three items (e.g., "The interface of ChatGPT is designed in a clear and intuitive way"), rated on a Likert scale from 1 ("strongly disagree") to 5 ("strongly agree"). The mono-factorial structure of the PEOU was tested with a CFA. The saturated model indicated that factor loadings were all high ($>.80$) and significant ($p <.001$). Internal consistency score was fair (McDonald's $\omega = .800$). The *attitude toward using ChatGPT* (A) was evaluated through five items (e.g., "I strongly support the use of ChatGPT by students for their university education"), rated on a Likert scale from 1 ("strongly disagree") to 5 ("strongly agree"). The mono-factorial structure of the A was tested with a CFA. Fit indices for this model were good [$\chi^2 (5) = 4.021$, $p = 0.5464$; RMSEA = 0.000 (0.000–0.061), $p = 0.890$; CFI = 1; SRMR = 0.010], confirming the monofactorial structure of the scale. The factor loadings were all high ($>|.60|$) and significant ($p <.001$). Internal consistency score was excellent (McDonald's $\omega = .905$). The *behavioral intentions to use ChatGPT* (BI) was evaluated through three items (e.g., "I intend to use ChatGPT in the future for my university studies"), rated on a Likert scale from 1 ("strongly disagree") to 5 ("strongly agree"). The mono-factorial structure of the BI was tested with a CFA. The factor loadings were all high ($>.90$) and significant (p

$<.001$) in the saturated model. Internal consistency score was excellent (McDonald's $\omega = .965$). To assess *ChatGPT academic use* (AU), we constructed one ad hoc item measured on a Likert scale from 1 ("never") to 5 ("often"): "How often have you used ChatGPT for your university learning?". The external variables were drawn from previous studies and evaluated on a Likert scale from 1 ("strongly disagree") to 5 ("strongly agree"). Specifically, *technology self-efficacy* (SE) was measured through four items taken from the study by Ni and Cheung (2023), for example: "I am able to use a new technology even if there is no one to show me how". The mono-factorial structure of the SE was tested with a CFA. Fit indices for this model were good [$\chi^2 (2) = 6.998$; $p = .0302$; RMSEA = 0.078 (0.021–0.145), $p = .171$; CFI = 0.994; SRMR = 0.012], confirming the mono-factorial structure of the scale. The factor loadings were all high (>0.70) and significant ($p <.001$). Internal consistency score was good (McDonald's $\omega = 0.887$). *Social norms related to technology use* (SN) were assessed through two items taken from the study by Aburbeian et al. (2022), for example: "Others' opinions about new technologies influence my intention to use them". These two items are adequately correlated with each other (Spearman $\rho = 0.452$). Finally, *technology anxiety* (AX) was evaluated through four items taken from Guner and Acarturk (2020), for example: "I hesitate to use new technologies for fear of making mistakes that I cannot correct". The monofactorial structure of the AX was tested with a CFA, the error terms between items 2 ("I'm scared of the idea of losing information due to a wrong operation while using new technology") and 3 ("I hesitate to use new technologies for fear of making mistakes that I cannot correct") were correlated. Fit indices for this model were good [$\chi^2 (1) = 1.516$; $p = .2183$; RMSEA = 0.036 (0.000–0.142), $p = .425$; CFI = 0.999; SRMR = 0.007], confirming the monofactorial structure of the scale. The factor loadings were all high (>0.50) and significant ($p <.001$). Internal consistency score was good (McDonald's $\omega = 0.830$). Additionally, one ad hoc item was constructed to assess university students' *knowledge of ChatGPT*, rated on a Likert scale from 1 ("never heard of it") to 5 ("yes, I know very well what it is"): "Have you ever heard of ChatGPT?". In this study, knowledge of ChatGPT was used as a control variable.

Data analysis

We estimated descriptive statistics for each variable of the study using SPSS (version 29.0.2.0; IBM Corp., 2023). After describing the data, for each of the six scales adopted (PU, PEOU, A, BI, SE, AX), we tested the factorial structure

and saved their factor scores. Finally, adopting these factor scores as observed variables, the relationships between variables were tested performing path analysis. All CFA and path analysis models were run in Mplus (version 7.11; Muthén & Muthén, 1998–2017). Maximum Likelihood (ML) was used as the estimator method and Full Information Maximum Likelihood (FIML) was used as the method to handle missing data. The dataset is available in the OSF page <https://doi.org/10.17605/OSF.IO/EMV58>.

Path analysis

A path analysis model was run on the total sample ($N=409$). In this model, the external variables (technology self-efficacy - SE, social norms related to technology use - SN, and technology anxiety - AX) were correlated with each other and were included as predictors of both the perceptions variables about ChatGPT (perceived usefulness - PU, and perceived ease of use - PEOU), as done by Aburbeian et al. (2022) Guner and Acarturk (2020) and Ni and Cheung (2023). Furthermore, as proposed by Davis' (1989) TAM model, (1) PEOU was included as predictor of both PU and attitude toward using ChatGPT (A); (2) PU was included as predictor of both A and behavioral intention to use ChatGPT (BI); (3) A was included as a predictor of BI too; (4) and finally BI was included as a predictor of the outcome (AU). In this model ChatGPT knowledge was included as control variable, as suggested by Venkatesh et al. (2000). Dataset is avai.

Results

Descriptive statistics

In Table 2, we reported the descriptive statistics for each variable investigated in this study.

Table 2 Descriptive Statistics^c

Technology self-efficacy (SE)	min max		M	S.D.
	1	5		
Social norms related to technology use (SN)	1	5	2.48	0.94
Technology anxiety (AX)	1	5	2.14	0.90
Knowledge of ChatGPT	1	5	3.58	1.13
Perceived usefulness of ChatGPT use (PU)	1	5	3.00	1.11
Perceived ease of ChatGPT use (PEOU)	1	5	3.61	0.88
Attitude toward using ChatGPT (A)	1	5	3.24	1.00
Behavioral intentions to use ChatGPT (BI)	1	5	2.90	1.26
ChatGPT academic use (AU)	1	5	1.82	1.22

^c $N=409$

Path analysis

Figure 3 showed the model tested. The model fits well the data [$\chi^2=43.761$, $df=13$, $p<.001$; RMSEA = 0.076 (0.052–0.101) $p=.039$; CFI = 0.982; SRMR = 0.024]. Regarding external variables (1), results show that:

- SE does not influence PU ($\beta=0.033$; $p=.514$) disproving hypothesis 1.1a, but it positively influences PEOU ($\beta=0.164$; $p<.001$), confirming hypothesis 1.1b.
- SN positively influences PU ($\beta=0.131$; $p=.004$) confirming hypothesis 1.2a, but does not influence PEOU ($\beta=-0.013$; $p=.767$), disconfirming hypothesis 1.2b.
- AX does not influence PU ($\beta=-0.085$; $p=.078$), disconfirming hypothesis 1.3a, but negatively influences PEOU ($\beta=-0.122$; $p=.006$), confirming hypothesis 1.3b.

Additionally, AX and SN are correlated (0.257; $p<.001$), as well as AX and SE (-0.236 ; $p<.001$), while SE and SN are not associated (-0.046 ; $p=.352$). Regarding the section related to user motivation (2), results show that:

- PEOU positively influences PU ($\beta=0.400$; $p<.001$), confirming hypothesis 2.1a, but does not influence A ($\beta=0.059$; $p=.087$), disconfirming hypothesis 2.1b.
- PU positively influences A ($\beta=0.809$; $p<.001$) and BI ($\beta=0.640$; $p<.001$), confirming both hypothesis 2.2a and 2.2b.
- A positively influences BI ($\beta=0.230$; $p<.001$), confirming hypothesis 2.3.
- BI positively influences AU ($\beta=0.541$; $p<.001$), confirming hypothesis 2.4.

We used knowledge of ChatGPT as a control variable, which significantly influences the following variables: SE ($\beta=0.418$; $p<.001$), AX ($\beta=-0.200$; $p<.001$), PEOU ($\beta=0.430$; $p<.001$), BI ($\beta=0.095$; $p<.001$) and AU ($\beta=0.318$; $p<.001$) (Fig 4).

Finally, regarding the indirect effects (in Table 3), the following are significant. A is indirectly influenced by all external variables, specifically by SE and AX via PEOU and PU, and by SN via PU. BI is indirectly influenced by both perceptions, specifically by PU via A, and by PEOU via both PU alone and PU and A together. Lastly, AU is indirectly influenced (1) by PU via both BI and A together as well as just BI; (2) by PEOU via both PU and BI, and PU, A, and BI; (3) and by A via BI.

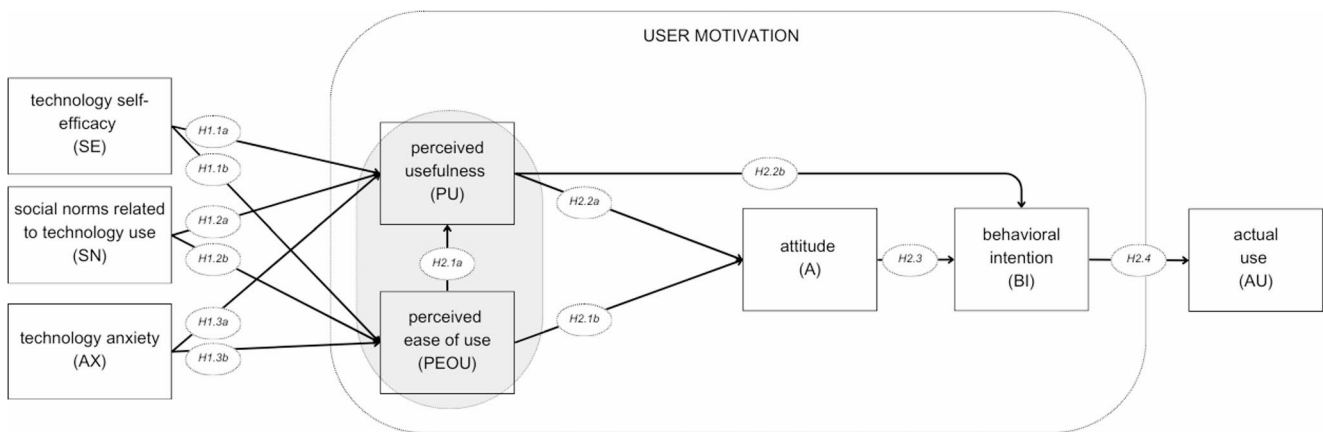


Fig. 3 Path model with ChatGPT knowledge as a control variable^{bb}Note that indirect effects are also estimated

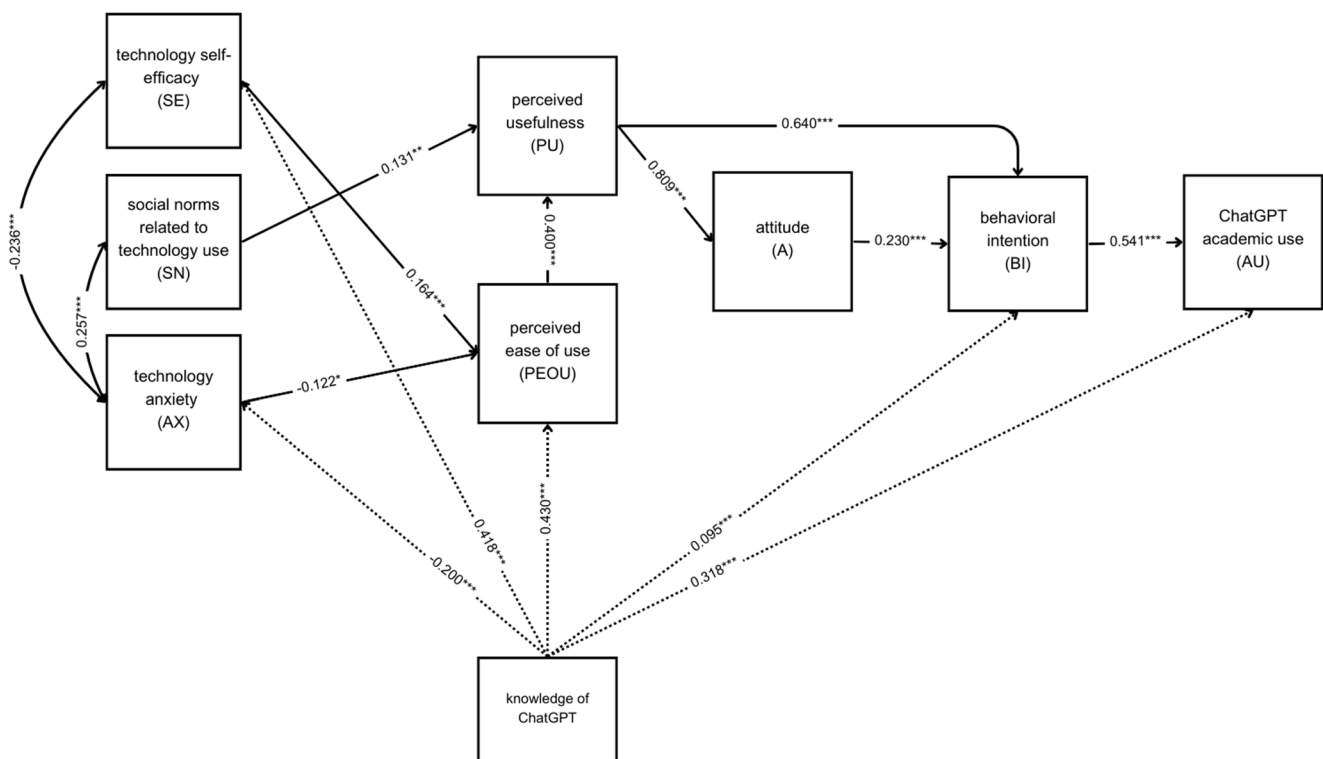


Fig. 4 Path model with ChatGPT knowledge as a control variable^c
^dNote. Only significant correlational and regression paths are represented (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). The dashed arrows in

black represent significant paths between the control variable and the TAM variables. Standardized values are reported. The indirect paths, which are in Table 3, are not reported in the figure

Discussion

Generative AI, particularly tools like ChatGPT, has rapidly emerged as a significant development in both technology and education. These tools are transforming the academic landscape by offering students new ways to access information, generate ideas, and enhance their learning experiences. However, despite the potential of these tools in academic contexts, little is known about university students'

intentions and actual use of ChatGPT. Investigating this is crucial because it can provide insights into how students interact with AI and how educators can better support its use. This study investigated the academic use of ChatGPT among 409 Italian university students using Davis's Technology Acceptance Model (TAM, 1989).

Although the survey was conducted at the beginning of the diffusion of ChatGPT in Italy, it was already well-known, with over 90% of students having at least heard

Table 3 Indirect Effects

		β (p)
SE INDIRECTLY INFLUENCES A	via PU	0.027 (0.514)
SE INDIRECTLY INFLUENCES A	via PEOU	0.010 (0.123)
SE INDIRECTLY INFLUENCES A	via PEOU and PU	0.053 (0.001)
SN INDIRECTLY INFLUENCES A	via PU	0.106 (0.004)
SN INDIRECTLY INFLUENCES A	via PEOU	−0.001 (0.770)
SN INDIRECTLY INFLUENCES A	via PU and PEOU	−0.004 (0.767)
AX INDIRECTLY INFLUENCES A	via PU	−0.069 (0.078)
AX INDIRECTLY INFLUENCES A	via PEOU	−0.007 (0.146)
AX INDIRECTLY INFLUENCES A	via PEOU and PU	−0.039 (0.009)
PU INDIRECTLY INFLUENCES BI	via A	0.186 (<0.001)
PEOU INDIRECTLY INFLUENCES BI	via PU	0.256 (<0.001)
PEOU INDIRECTLY INFLUENCES BI	via A	−0.014 (0.104)
PEOU INDIRECTLY INFLUENCES BI	via PU and A	0.074 (<0.001)
PU INDIRECTLY INFLUENCES AU	via BI	0.346 (<0.001)
PU INDIRECTLY INFLUENCES AU	via A and BI	0.101 (<0.001)
PEOU INDIRECTLY INFLUENCES AU	via PU and BI	0.138 (<0.001)
PEOU INDIRECTLY INFLUENCES AU	via BI and A	0.007 (0.105)
PEOU INDIRECTLY INFLUENCES AU	via PU and A and BI	0.040 (<0.001)
A INDIRECTLY INFLUENCES AU	via BI	0.124 (<0.001)

of it. However, actual use in academic contexts remained low, with an average rating of 1.82 out of 5 ($SD=1.22$). This contrasts with the expressed attitude toward using it ($M=3.24$, $SD=1.00$) and intention to use it in the near future, which was notably higher ($M=2.90$, $SD=1.26$). This suggests that ChatGPT is likely more widely used now than it was in 2023, and we can anticipate a continued increase in its adoption.

Whereas previous studies have adopted different configurations of TAM to examine ChatGPT adoption, our study advances this line of research by testing a more complex path analysis model that incorporates both the full set of core variables and additional predictors. This allowed us to clarify the direct and indirect pathways influencing intention and actual use more comprehensively than in prior research.

The path analysis model we tested helps us understand which variables facilitate or hinder the intention and the actual use of ChatGPT in the academic context. With regard to the core variables of the TAM model, the intention to use ChatGPT, which significantly predicts its actual use (0.541), is higher in university students who have a positive attitude toward ChatGPT (0.230) and perceive it as useful (0.640). These paths are consistent with the findings of Albayati (2024) and Liu and Ma (2024), who employed a TAM model including attitude, and with Duong et al. (2023) and Liu and Ma (2024), who also modeled actual use. In line with classic TAM research (e.g., Venkatesh & Davis,

2000), we found that perceived usefulness of the technology tool is a key factor in the model. In particular, perceived usefulness of ChatGPT in academic context affects directly both attitude toward this tool and the intention to use it, and indirectly the actual use of ChatGPT. Perceived usefulness thus emerges as a variable to focus on when aiming to support the use of ChatGPT among students.

Turning to the external variables, our contribution lies in demonstrating that psychological and social antecedents influence the two TAM beliefs in differentiated ways. Students who view ChatGPT as a useful tool in academic context have higher levels of social norm related to technology use (0.131), and perceive ChatGPT as easier to use (0.400). In turn, this perception of ease of use is predicted by high technology self-efficacy (0.164) and low technology anxiety (−0.122). These results extend the findings of Liu and Ma (2024) and Duong et al. (2023), who did not include external variables, and Albayati (2024), who considered external variables but did not model actual use.

The findings largely confirm the hypotheses of TAM, with some exceptions. We found that technology self-efficacy does not influence the perception of ChatGPT's usefulness. Therefore, the perception that using ChatGPT is useful is independent of how technologically self-efficient one feels. On the other hand, the perception that ChatGPT is easy to use is significantly influenced by technology self-efficacy. This result is consistent with previous studies, which indicate that confidence in one's technical abilities can reduce perceived barriers to using new technologies (Scherer et al., 2019).

Social norms related to technology use influence perceived usefulness but not perceived ease of use, which may indicate that others' opinions about technology affect perceptions of its usefulness more than its ease of use. This might be because recommendations and shared experiences can convince students of ChatGPT's added value without directly impacting their perception of its ease of use (Schepers & Wetzels, 2007). Furthermore, we speculate that this can also depend on social norms being mainly developed through social media. Here students are exposed to contents that stress what can be done with ChatGPT, but not necessarily how easy it is. In this sense, shared experiences often focus on the tool's potential rather than its usability.

Technology anxiety negatively impacts perceived ease of use but not perceived usefulness, suggesting that concerns related to technology use make it harder to perceive ChatGPT as easy to use without significantly affecting perceptions of its usefulness. This suggests that technology anxiety can be a significant barrier to adopting new technologies.

In sum, our study shows that the external variables examined (SE, SN, AX) affect only one of the two core perceptions of ChatGPT (PU and PEOU). Specifically,

self-efficacy and anxiety shape perceptions of ease of use, while social norms influence perceptions of usefulness. This finding is consistent with previous research conducted in other technological domains, which has suggested that PU and PEOU are explained by distinct predictors (e.g., Aburbeian et al., 2022; Schepers & Wetzels, 2006; Venkatesh & Davis, 2000). By integrating these external factors into the complete TAM sequence from PEOU to PU, A, BI, and AU, our model refines TAM by clarifying the differentiated antecedents of its two core beliefs and strengthens its explanatory coherence when applied to generative AI in higher education.

Limitations and future studies

This study has several limitations that should be considered. First, the sample was limited to Italian university students, which may restrict the generalizability of the results to other populations or cultural contexts. Additionally, the use of non-probability sampling may have introduced selection bias. In particular, we initially relied on snowball sampling but later integrated Prolific recruitment to reach the required sample size within the limited timeframe of ChatGPT's early adoption phase; while this strategy ensured adequate statistical power, it may also have introduced heterogeneity in participant recruitment. Furthermore, the data were cross-sectional, which limits our ability to draw definitive conclusions about causal relationships between the variables. Moreover, actual use of ChatGPT was measured through self-reports rather than behavioral logs, which may be affected by recall or social desirability biases. Furthermore, this construct was operationalized using a single-item measure, potentially limiting reliability and content coverage. Future studies could benefit from triangulating self-reported usage with objective digital trace data and multi-item behavioral measures. Because all variables were collected through the same self-report survey, common method variance cannot be ruled out. Finally, social norms related to technology use were assessed with a brief two-item measure, and future research would benefit from employing broader validated instruments. It is also important to note that the study was conducted when ChatGPT was still relatively underused, which may have affected the findings regarding its adoption and impact.

Future studies could expand the sample to different populations and international contexts to verify the generalizability of the results. Future research should also consider different educational levels, such as high schools, and various external factors specific to different contexts. Examining how these variables influence the use and perception of ChatGPT in varied settings could provide a more

comprehensive understanding of its impact across different demographic and educational backgrounds. Finally, we believe that future studies should not only understand what facilitates ChatGPT use in academic settings but also identify strategies to guarantee its ethical use. In particular, the scientific community must understand how to cultivate responsible AI use in academic settings, ensuring that generative AI becomes a tool that enhances learning without compromising academic integrity.

Implications

Practical and educational implications

Experts predict that the adoption of tools like ChatGPT will increase in the near future, making it imperative to understand which students are more inclined to use them (Yusuf et al., 2024). Our study suggests that students who perceive ChatGPT's usefulness are more intentioned to use it. By identifying these students, they can be leveraged as peer leaders who can help others integrate AI into their academic workflows, making the tool accessible to all.

Furthermore, our findings suggest that the intention to use ChatGPT can be enhanced among students by increasing their technology self-efficacy and social norms related to technology, as well as reducing technology anxiety. These are all significant predictors that directly affect the perceptions about ChatGPT. In particular, given the impact of technology self-efficacy, it is crucial to provide ongoing training and support to students to enhance their confidence in using technology tools. Institutions should consider promotional strategies that leverage social norms, such as peer testimonials and informational campaigns, to increase perceptions of ChatGPT's usefulness. Finally, it is important to implement measures that reduce technology anxiety, such as detailed tutorials and easily accessible technical support, to facilitate wider adoption of ChatGPT.

It is also worth noting that institutions should also develop and enforce ethical guidelines for the use of ChatGPT to ensure responsible usage. Fostering a culture of ethical awareness around AI technologies through workshops and seminars can help students navigate the ethical challenges associated with AI use.

Taken together, these implications highlight that interventions will be most effective if implemented simultaneously: improving confidence (self-efficacy), shaping social environments (norms), and reducing barriers (anxiety) while also ensuring ethical awareness. Only by acting on these multiple fronts can universities expect to achieve meaningful and sustained improvements in students' adoption of AI tools and, ultimately, in their learning outcomes.

Theoretical implications for TAM research

Beyond practical recommendations, our findings also contribute to the literature on TAM. By combining external antecedents with the full TAM chain, our study shows that ChatGPT adoption can be explained not only by core cognitive beliefs but also by psychological barriers (e.g., anxiety, self-efficacy) and social influences (e.g., norms).

For researchers, this case further illustrates both the strength and the weakness of TAM. On the one hand, the flexibility of TAM allows it to be adapted to different technologies and contexts, making it a versatile theoretical framework. On the other hand, this very flexibility creates problems of comparability: not all studies use the same set of constructs, measurement items, or analytical techniques. As seen in prior ChatGPT studies, some included attitude, others excluded it; some added external variables, others did not; and different scales or statistical approaches (e.g., SEM vs. regression) were employed. These inconsistencies complicate cross-study comparisons and limit the accumulation of evidence.

Future TAM research would benefit from greater harmonization in measurement and design choices. Agreeing on common operationalizations of PU, PEOU, and related constructs would enhance comparability across studies, while maintaining the flexibility to introduce well-justified context-specific extensions. In this way, TAM can continue to evolve as a robust yet coherent framework for studying the acceptance of emerging technologies such as generative AI.

Conclusions

The rapid advancement of generative AI has revolutionized numerous domains, including education. This study investigates the adoption of ChatGPT, a prominent generative AI tool, among Italian university students using the Technology Acceptance Model (TAM) as a theoretical framework. Our findings highlight the importance of perceived usefulness in predicting the attitude, the intention to use and the actual use of ChatGPT. Furthermore, the results provide useful insights for academic institutions, highlighting the need for them to promote the adoption of ChatGPT encouraging critical and responsible use of the tool. These insights contribute to fostering a more inclusive and effective educational environment, ensuring that students engage with AI in a manner that supports their academic development while being mindful of its broader implications.

Finally, this study contributes to the refinement of TAM by enhancing both internal and external validity. Internal validity was strengthened by controlling for prior knowledge of ChatGPT, a critical factor during the early adoption

phase. External validity was advanced by testing TAM with novel external variables not included in previous ChatGPT studies, and by doing so in a new population—Italian university students—at an early stage of diffusion. Together, these contributions broaden the applicability of TAM to disruptive AI technologies and diverse educational contexts.

Author contributions Margherita Lanz and Angela Sorgente contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Rossella Caliciuri and Martina Milani, with contributions from Margherita Lanz and Angela Sorgente. The first draft of the manuscript was written by Rossella Caliciuri and Rosario Rodriguez, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Data availability The dataset is publicly available on the Open Science Framework (OSF): <https://doi.org/10.17605/OSF.IO/EMV58>.

Declarations

Ethics approval The study protocol was approved by the Ethical Committee of the Department of Psychology of Università Cattolica del Sacro Cuore and was conducted in accordance with the ethical standards of the 1964 Declaration of Helsinki and its later amendments.

Consent to participate Informed consent was obtained from all individual participants included in the study.

Consent to publish All authors have read and approved the final manuscript and consent to its publication.

Conflict of interest The authors declare that they have no financial or proprietary interests in any material discussed in this article.

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