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The General Attitudes towards Artificial Intelligence Scale (GAAIS): validation and psychometric properties analysis in the Italian context

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Abstract
This two-study investigation aimed to assess the psychometric properties of the Italian version of the General Attitudes towards Artificial Intelligence Scale (GAAIS). In study 1 ($N=236$ adults) confirmatory factor analysis (CFA) was conducted to examine the factorial structure of the scale. Study 2 ($N=177$) assessed the concurrent and predictive validity of GAAIS. Concurrent validity was examined by correlating positive and negative attitude scores toward AI with another measure of attitude toward AI. Predictive validity was assessed by measuring the predictive ability of attitude on intention to use AI. The findings support the two-factor model, including for this Italian version of the scale consistent with the original one (Study 1). Moreover, positive attitudes towards artificial intelligence, as measured by the GAAIS positive factor, were positively correlated with general attitudes towards the use of AI, while the negative factor showed a significant negative correlation with the same general attitudes (Study 2). Then, the Italian version of the GAAIS can be considered as a valid tool for assessing people orientations towards artificial intelligence in the context analyzed, confirming the relevance of studying attitudes and its measurement towards artificial intelligence in different cultural contexts. This measure which relates to a strong psychosocial perspective, may support future research to deepen the understanding of the factors influencing attitudes towards AI as well as to develop more effective communication and training program interventions, being this a very crucial topic in actual society.

Keywords Artificial intelligence, Psychometric properties of Italian attitude scale, Attitudes toward AI, Intentions to use artificial intelligence, Technology acceptance model

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Introduction

The extensive integration of artificial intelligence (AI) into many fields of modern society highlights its relevance both as a technological advancement and as a subject of academic research across several disciplines. AI now underpins devices, systems, and applications that individuals interact with on a daily basis, influencing multiple aspects of their lives, from consumer behavior to industrial processes [1–4], as well as contributing to learning purposes and organizational human resources management systems [5–7]. The integration of AI into everyday life is following diverse trajectories, including pervasive robotization, ubiquitous online data access, empowered edge computing, smart spaces, and digital ethics. These trends are shaping research on artificial intelligence and its applications, profoundly influencing our daily lives, our cities, and even our leisure time [8]. Nevertheless, artificial intelligence is still associated with popular misconceptions that cause the public to either have unrealistic fears or excessive expectations about how it will change our workplace and life in general [9]. AI applications and innovations have the potential to enhance our lifestyle in multiple ways, as demonstrated by models for assessing the relevance of opinions in uncertainty and info-incompleteness conditions, and frameworks for stock price prediction supported by sentiment classifiers based on news headlines and tweets [8]. The rapid evolution of artificial intelligence raises the question of whether we are adequately preparing society to positively integrate these technologies, through principles, policies, incentives, and ethical frameworks necessary for society to enjoy the benefits of AI while minimizing the risks associated with its use [10].

Consequently, researchers from a social psychological perspective are focusing on AI to analyze the main psychological factors influencing people's behaviors and habits toward this new technology. The attitudes are a critical psychological concept that previous studies have underlined as a factor influencing the human-technology interactions (e.g., Technology Acceptance Model - TAM) [11]. Also, attitudes are relevant factors to be analyzed within the new frame of AI's studies leading to a better understanding of the adoption and diffusion of AI technologies. Moreover, this analysis could be helpful for the ethical framework and regulatory policies governing AI's development and implementation [4, 11].

Human perception of AI is shaped by a complex interplay between attitudes and concerns. While AI is hailed for its potential to drive innovation, boost productivity, and solve complex problems [12], there are uncertainties about its impact on aspects such as employability and privacy, on more sensitive social issues such as the ability of machines to make decisions autonomously [13–17] as well as on potential risks. Recent research suggests that attitudes toward AI technologies are significantly shaped by perceived humanness and interactivity features [18]. These findings complement our investigation of general attitudes toward AI by highlighting specific factors that may influence the formation of such attitudes. Also, studies on AI's impact on daily life reveal positive influences across various sectors such as work, education, and daily applications. While AI affects job displacement, its overall impact is found to be minor outside of work environments. A promising pattern of adaptation, coexistence, and collaboration between AI and humans emerges, suggesting a positive future direction [8]. However, despite the widespread use of AI in various applications, recent advancements indicate that the field is still in its early stages of development, with many opportunities for growth and future innovation ahead [8]. Furthermore, Cave and Dihal [19] reveal how cultural and racial biases influence AI perception, demonstrating that the predominant portrayal of AI as "white" shapes public understanding and acceptance of these technologies. Gerlich [20] conducted a comprehensive study across multiple countries (US, UK, Germany, and Switzerland) that revealed significant variations in AI perception based on trust levels and cultural backgrounds. Also, recent systematic reviews on AI acceptance have highlighted the multifaceted nature of factors that shape attitudes toward this technology [21]. Perceived usefulness, performance expectancy, attitudes, trust, and effort expectancy have been identified as significant predictors of behavioral intention, willingness, and actual use behavior of AI across multiple industries. Then, trust and attitudes seem to be equally important in shaping the acceptance of AI, and therefore the predisposition to its use, by users [22] Additionally, the latest theoretical models propose that AI acceptance should be examined through three distinct perspectives: user-centered acceptance, delegation acceptance, and societal adoption acceptance [23]. These perspectives reflect different ways in which individuals interact with AI technologies—as direct users, as delegators of tasks, or as members of society affected by its broader implementation.

By investigating people's attitudes, we can therefore better explain the decisional process and behavior of both individuals and communities [24, 25], an interest that has already been explored by former studies that have focused on factors capable of influencing similar attitudes, such as demographic, personality and trust-related aspects [4, 26–28]. In this context, Ajzen's Theory of Planned Behavior (TPB) [29] is configured as a starting theoretical framework to explore those factors that predispose people to adopt technologies such as AI. In particular, the TPB states how the intention to adopt a behavior depends on three main factors: the attitude towards the behavior itself, the subjective norms and the perception of one's control over that behavior [29]. The attitude refers to the general evaluations of an individual towards the behavior in question, while the subjective norms concern the perception of other people's expectations, and the perception of behavioral control reflects the confidence of possessing useful skills and resources to carry out the behavior [29]. In the field of AI, specifically, attitude plays a primary role as people can develop both positive perceptions (related to the efficiency and opportunity offered by the technology) and negative ones (related to ethical and occupational concerns) [4] sufficient to predict intention to use. This sense of control is particularly relevant in the context of AI, where perceived autonomy of systems can trigger concerns. According to Gerlich [20], public perception of AI exhibits a significant correlation between societal interpretations of AI's impact and factors like trustworthiness, perceived risks, and usage/acceptance. His study demonstrates that individuals who perceive AI as threatening tend to have a more pessimistic outlook on its potential outcomes, while proponents recognize its transformative capabilities. These inclinations are deeply connected to both trust and the perceived uniqueness of AI compared to previous technologies. Attitudes towards artificial intelligence are particularly relevant in the current technological landscape, as AI adoption is not always an individual choice, and AI systems are rapidly changing how people interact with technology. This raises important questions about social acceptance of AI and society's preparation for a "good AI society," with growing public and scientific interest in the principles, policies, incentives, and ethical frameworks required [10]. Recent research shows that, although there are concerns about AI's impact on aspects such as employment, its influence is perceived positively in areas such as education, healthcare, and improvement of daily life quality [9]. The acceptance of AI technologies is also influenced by cultural and contextual factors. Tran and colleagues [30] demonstrated that in some cultural scenarios, the need for human contact cannot be replicated or replaced by AI regardless of its perceived usefulness or ease of use. This finding suggests that AI acceptance models need to account for cultural implications where tradition and human interaction are highly valued. Additionally, trust in the organizations deploying AI systems often proves more influential than trust in the technology itself, especially in public sector applications [31, 32].

In line with this theoretical framework, the role of attitudes in predicting intention to use has been analyzed more specifically with regard to the adoption of technologies using Davis' Technology Acceptance Model (TAM) [33]. This model postulates that the adoption of a technology depends on the degree to which the individual believes it can improve their performance and the ease thanks to which it can be used. Applying the TAM to the AI's context, therefore, it is clear how the perception of usefulness could be influenced by aspects such as economic opportunities or the offer of performance improvement, while the perception of complexity in adopting such technology, or the low degree of control one has over it, could inhibit the intention to use it. However, it is important to consider that AI's adoption is not always an individual choice, as in many cases the implementation of such technology can be determined by external decisions taken by governments or large companies, limiting the free will of the end users [4, 34, 35]. This particularity of AI raises important issues related to control and trust, two factors that deeply influence psychological responses towards the adoption of this technology [27, 28]. In this scenario, AI's ability to make autonomous decisions distinguishes it from more traditional technologies, which raises new insights and requires in-depth analysis on how people develop their attitudes towards this technology [36].

While several tools have been developed in the past to measure general technology acceptance [33, 37], many of these do not focus on the more recent concept of AI. Historically, technology acceptance has focused on individuals' willingness to adopt new technologies for their own personal use, whereas today AI represents a different challenge, with applications often socially imposed without explicit consent from end-users [38, 39]. As a result, people's attitudes towards AI are taking on an increasingly nuclear role in determining the acceptance and integration of this technology into everyday life.

The *General Attitudes towards Artificial Intelligence Scale* (GAAIS), developed by Schepman and Rodway [4, 28] replies to the need for a reliable means to measure population's attitudes towards AI. Their scale is composed of two main subscales: the *Positive GAAIS*, which measures favorable attitudes such as the perception of opportunities, and the *Negative GAAIS*, which detects concerns and negative emotions such as discomfort or fear. The use of this tool allows us to evaluate how people balance these two dimensions in forming their overall attitude towards AI, ultimately it may predict their intention to use it.

This study aims to validate the Italian version of the *GAAIS* and to explore the construct of attitudes towards AI within the Italian context. The validation of AI attitude measures across different cultural contexts is increasingly important as AI anxiety manifests differently based on cultural perceptions of technology [40]. In the Italian context, validating the GAAIS provides an essential tool for measuring attitudes that may predict levels of AI anxiety and concerns, and the subsequent behavioral responses. The objective, then, is to gain a deeper understanding of how these attitudes can influence the intention to use AI by analyzing the underlying dimensions of positive and negative perceptions. This investigation not only provides insights into the structure of attitudes towards AI, but also highlights their role in shaping behavioral intentions, contributing to the broader discourse on the acceptance and integration of AI into society.

To date, the GAAIS has been validated outside of its original English-speaking context. In particular, Kaya et al. [26] developed and validated a Turkish version of the GAAIS, which had a factor structure that was consistent with the original two factors model. Although the factorial validity of the Turkish adaptation was preserved, the authors considered how cultural and societal characteristics could influence attitudes towards AI. For instance, the impact of religious values and the lack of public knowledge regarding AI's inner workings were posited as pertinent contextual factors. While these elements did not impose changes on the scale structure, they highlight the role of cultural dimensions in their results interpretation.

These insights support the necessity to broaden the adaptation and validation of the GAAIS in other cultural contexts, such as Italy, because of the distinctive cultural and societal determinants present there. Italy has historically been cautious about technological advancement as reflected in its comparatively slower initial adoption rate among the European nations, according to the European Innovation Scoreboard Report 2024 provided by European Commission [41]. The Annual Surveys conducted by the national Institute of Statistics (ISTAT) have shown on one side that Italian citizens frequently raise concerns about new technologies' effects on labor security and conventional job positions and, on the other side, a level of digital competencies below the European average in the 2023 reports [e.g., 42]. This confirms that the growth of human capital competencies is a very strategic topic to deal with in Italy, as a European country. Italy exhibits robust cultural values that support interpersonal relations, direct interaction, and craftsmanship; these can be considered further elements which can shape attitudes towards independent, machine-led processes. Such cultural features then, can potentially infuse distrust in substituting human labor with artificial systems, particularly in domains where personal engagement and skilled craftsmanship are conventionally appreciated. Recent studies, in fact, have already underlined that cultural and context variables may play such a role in people's responses to AI, supporting the application of cultural theory to attitudes towards AI (e.g [43]).,. Therefore, examining perceptions of Artificial Intelligence in the Italian context is necessary for determining particular fears and acceptance patterns that will be substantially different from those observed in cultures with a more positive attitude towards technology. This validation, then, may address the demand for context-specific instruments that can assist policymakers, organizations, and educators in customizing efforts towards the development of wise and critical adoption of AI.

Aims of the study

This research aims to evaluate the psychometric properties of the Italian version of the General Attitudes towards Artificial Intelligence Scale (GAAIS) in Italian context. Two studies were conducted: the first study employed confirmatory factor analysis (CFA) to examine the factor structure of the GAAIS to verify the presence of a bifactorial composition measured by the scale. The second study assessed the concurrent and predictive validity of GAAIS. Concurrent validity was examined by correlating positive and negative attitude scores toward AI with another measure of attitude towards AI. Predictive validity was assessed by measuring the predictive ability of attitude on intention to use AI.

Study 1: confirmatory factor analysis

Method

Sample size determination

Determining the appropriate sample size or power of the study is of primary importance in research design [44]. In this study the a priori sample size was calculated using Soper's [45] online calculator for structural equation models. Based on an anticipated effect size of 0.30, a desired statistical power of 0.95, two latent variables, 20 observed variables, and a significance level of $\alpha = 0.05$, the minimum sample size required to detect the specified effect was 147.

Participants and procedures

Once the minimum sample size was determined and the research protocol was constructed, participants were voluntarily contacted during the academic year 2023–2024 and requested to complete an online questionnaire specifically structured using an online data collection platform. Data collection was conducted automatically and centralized in an online spreadsheet, ensuring efficiency and accuracy in managing the responses. Participants were students and other adult individuals recruited by those students who had expressed interest in the aims of the present research. Each respondent explicitly and comprehensively declared and marked their consent to participate and to the anonymous processing of their data before starting to fill in the questionnaire.

The inclusion criteria for the present study were as follows: (1) Native Italian speakers, (2) Legal age (in Italy, legal age is attained at 18 years) and (3) Consent to data collection and processing.

The final sample of the study comprised a total of 236 participants, with 127 identifying as female and 109 identifying as male. Participants' ages ranged from 19 to 65 years ($M = 28.17$; $SD = 12.71$). Regarding educational attainment, the majority of participants (184) held a lower secondary school diploma. Among the remaining participants, 44 held a bachelor's or master's degree, 5 held a doctoral degree or master's degree, and 3 participants held a primary school diploma. Nearly half of the participants were unemployed or seeking their first job (170), while the others were employed (66). Regarding the use of artificial intelligence (AI) in daily life, most participants reported engaging with it on a regular basis. Specifically, 64 individuals indicated using AI on a daily basis, while 60 reported using it several times a week. A total of 52 participants stated that they use AI several times a month, and 50 reported using it rarely. Only 10 participants indicated that they never use AI.

Ethical considerations and transparency

The authors of this study respected the ethical principles of the ethical code of the Italian Association of Psychology (AIP); furthermore, the study was submitted to the ethics committee of the University of Catania for evaluation. The ethics committee approved the study as it posed no risk to the health of the participants (approval number: Ierb-Edunict-2024.06.03/07). The datasets analysed during the current study are available in the Open Science Framework (OSF) repository webpage https://osf.io/6ex2h/?view_only=5ab73fa315824e20836a459f4ea7b8a2.

Measures

The questionnaire used for data collection contained the following section and measures:

Sociodemographic data. A first part of the questionnaire gathered background sociodemographic information, including gender, age, educational level, and employment status. Respondents were further queried about their prior experience with Artificial Intelligence (AI) systems in their daily lives. Specifically, they were asked to indicate how often they used AI in their daily lives, answering on a Likert scale ranging from 1 (never) to 5 (daily).

General attitudes towards AI. To gauge participants' attitudes towards Artificial Intelligence (AI), we employed the 20-item version of the GAAIS (*General Attitude towards Artificial Intelligence Scale*) developed by Schepman and Rodway [28]. The GAAIS comprises 12 positive items, which explore perceptions of opportunities, benefits, and positive emotions associated with AI adoption (e.g., *"Artificial Intelligence can provide new economic opportunities for this country"*); additionally, the scale includes 8 negative items which focus on concerns and negative emotions regarding AI use (e.g., *"I think artificially intelligent systems make many errors"*). Respondents rated each item on a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The definition of the Italian version was done by a mother tongue teacher with the back translation method as a first step, then it was completed and reviewed by three Italian researchers. This procedure allowed us to define the final version of the used scale.

Data analysis

For each item, we calculated descriptive statistics, including skewness and kurtosis values. Values between −2 and 2 indicate a normal distribution of the data [46].

Confirmatory Factor Analysis (CFA) was conducted using AMOS 22.0.0. To compare and select the best fitting model, two models were tested: a one-factor model and a two-factor model. The two-factor model was expected with best fit indices compared to the one-factor model. Model fit was assessed using several indices: the ratio of chi squared to degrees of freedom which should fall between 1 and 3; the Comparative Fit Index (CFI [47]), which should be greater than 0.90 [47, 48]; the Root Mean Square Error of Approximation (RMSEA; [49]) and the Standardized Root Mean Square Residual (SRMR; [50]), both of which should be less than 0.08 [49, 50]. To compare the models, the Akaike Information Criterion (AIC; [51]) was used, with lower values indicating a better fit [52]. Differences in AIC greater than 2 suggest that the differences between models are statistically significant [53].

The reliability of the measure was assessed by calculating McDonald's Omega (ω) values and Cronbach's Alpha values for each factor.

Results

Table 1 presents the descriptive statistics (mean and standard deviation) for the GAAIS's items. The score distribution approximated normality, as evidenced by the skewness and kurtosis values falling within acceptable ranges: minimum skewness was − 1.41 (item 5) and maximum was 0.58 (item 1); minimum kurtosis was − 1.15 (item 8) and maximum was 1.96 (item 5).

Model 1 (unidimensional) showed a poor fit to the data [$\chi^2_{(170)} = 884.25$, $\chi^2/df = 5.20$; $SRMR = 0.124$; $RMSEA = 0.134$ (90% $CI = 0.125–0.142$); $CFI = 0.591$]. Model 2 (two-factor) demonstrated a significant improvement in fit indices, although still at the threshold of acceptability [$\chi^2_{(169)} = 405.44$, $\chi^2/df = 2.40$; $SRMR = 0.076$; $RMSEA = 0.077$ (90% $CI = 0.068–0.087$); $CFI = 0.865$]. To further improve the fit of the two-factor model, a third model (Model 3) was tested. This model retained the two-factor structure and included correlated error terms between two pairs of items (items 13

Table 1 Descriptive statistics

	M	DS	Skewness	Kurtosis
GAAIS1	2.38	1.34	0.58	−0.85
GAAIS2	3.20	1.05	−0.25	−0.31
GAAIS3	3.24	0.95	0.01	−0.01
GAAIS4	2.55	1.03	0.14	−0.51
GAAIS5	4.25	0.95	-1.41	1.96
GAAIS6	3.26	0.96	−0.03	−0.33
GAAIS7	3.11	1.16	−0.06	−0.77
GAAIS8	3.31	1.34	−0.26	-1.15
GAAIS9	3.02	1.31	−0.11	-1.13
GAAIS10	3.25	1.17	−0.33	−0.65
GAAIS11	3.34	0.97	−0.38	−0.10
GAAIS12	3.28	1.09	−0.22	−0.43
GAAIS13	2.64	1.16	0.20	−0.77
GAAIS14	3.82	0.86	−0.53	0.16
GAAIS15	3.38	1.23	−0.30	−0.85
GAAIS16	2.56	1.05	0.15	−0.56
GAAIS17	2.96	1.04	−0.04	−0.63
GAAIS18	2.58	1.26	0.34	−0.89
GAAIS19	2.88	1.10	0.26	−0.51
GAAIS20	2.67	1.17	0.13	−0.89

Note. M = Mean; DS = Standard deviation

and 16; items 3 and 6). Model 3 showed an additional improvement in model fit, with all indices reaching satisfactory levels [$\chi^2_{(167)} = 329.10$, $\chi^2/df = 1.97$; SRMR = 0.070; RMSEA = 0.064 (90% CI = 0.054–0.074); CFI = 0.907]. The correlated residuals between item pairs 3 and 6, and 13 and 16 were added based on theoretical and semantic overlap. Items 3 ("Organizations use AI unethically") and 6 ("I think AI systems make many mistakes") both reflect a critical stance towards AI, addressing concerns related to ethical practices and system reliability, respectively. Similarly, items 13 ("An AI-powered operator would be better than an employee in many routine jobs") and 16 ("AI systems can perform better than humans") both convey a positive evaluation of AI performance, particularly in comparison with human workers. These items emphasize the perceived superiority of AI in task execution, leading to overlapping content and a stronger semantic association. The inclusion of these correlated residuals enhanced model fit. Standardized factor loadings, latent factor correlations, and residual error correlations are reported in the supplementary tables (see Supplementary material 1).

These findings support the adequacy of the modified two-factor model as a more parsimonious and better-fitting representation of the data.

McDonald's Omega coefficients were 0.86 (factor 1, positive) and 0.86 (factor 2, negative). Cronbach's Alpha values were 0.85 (factor 1, positive) and 0.85 (factor 2, negative).

Study 2: concurrent and predictive validity

Method

Sample size determination

The minimum required sample size for this study was determined a priori using G*Power Version 3.1.9.7 [54, 55]. Based on a bivariate normal model for correlation, with an alpha level of 0.05, a power of 0.80, and an expected effect size of 0.20 (i.e., between small and medium), the analysis indicated that a minimum of 153 participants was needed.

Participants and procedures

The same procedure as in Study 1 was applied to collect data in this study during the academic year 2024–2025. The final sample of the study comprised a total of 177 participants, with 113 identifying as female, 60 identifying as male and 4 as other. Participants' ages ranged from 19 to 69 years (M = 33.47; SD = 14.51). Regarding educational attainment, the majority of participants (114) held a lower secondary school diploma. Among the remaining participants, 46 held a bachelor's or master's degree, 3 held a doctoral degree or master's degree, and 14 participants held a primary school diploma. Ninety-four of the participants were unemployed or seeking their first job, while the others were employed (83). Regarding the use of artificial intelligence (AI), 68 participants reported using AI every day, 54 participants use it several times a week, 36 stated that they use it several times a month, and 13 reported using it rarely. Only 6 participants indicated that they never use AI.

Ethical considerations and transparency

The ethical considerations applied in Study 1 were equally observed in the present study. The datasets analysed during the current study are available in the Open Science Framework (OSF) repository webpage https://osf.io/6ex2h/?view_only=5ab73fa315824e20836a459f4ea7b8a2.

Measures

The questionnaire used for data collection contained the following section and measures:

Sociodemographic data. The same demographic statistics were collected as in Study 1.

*General attitudes towards AI (*Schepman & Rodway [28]; Italian version from Study 1). In this study McDonald's Omega coefficients were 0.86 for factor 1 (positive) and 0.84 for factor 2 (negative). Cronbach's Alpha (**α**) values were 0.86 (factor 1, positive) and 0.83 (factor 2, negative).

Attitudes towards the use of AI were measured through semantic differential items already used in similar research on people's habits of using other tools (e.g [56, 57])., introduced by the following statement: "For me, using AI is:". Responses were given on a 7-point bipolar

Table 2 Correlations between the two factors of GAAIS and attitudes towards the use of AI

	Attitudes towards the use of artificial intelligence
GAAIS positive	0.57**
GAAIS negative	−0.31*

** $p < 0.01$; * $p < 0.05$

scale with the following adjectives: unpleasant/pleasant, unlikable/likable, unsatisfactory/satisfying, unimportant/important, useless/useful". High scores indicate a positive attitude towards the use of AI. McDonald's Omega in this study is 0.93. Cronbach's Alpha value in this study was 0.93.

Intentions to use AI were measured using a single item ("My intention to start/continue using AI is high") adapted from Baeli et al. [56]. Respondents rate their agreement on a 7-point Likert scale (from 1 = *strongly disagree* to 7 = *strongly agree*).

Data analysis

Concurrent validity was assessed by investigating the correlation with a similar measure of attitude towards Artificial Intelligence (measured through a different tool based on semantic differential). Specifically, since a measure of positive attitude towards Artificial Intelligence was used, a positive correlation with the positive factor and a negative correlation with the negative factor were expected.

Predictive validity was assessed by investigating the potential predictive capacity of positive factor and negative factor for the intentions to use artificial intelligence. Then, based on the reference literature and our aim the two relationships between the positive factor of GAAIS and the intentions to use artificial intelligence, and between the negative factor of GAAIS with the same intention to use artificial intelligence, have been analysed.

Results

As expected, the attitudes towards the use of artificial intelligence positively correlates with the positive factor of GAAIS and negatively with the negative factor of GAAIS. The analysis is shown in Table 2.

As shown in Table 3, the positive attitude towards artificial intelligence (GAIS positive) accounted for a substantial proportion of the variance in the intention to use AI ($R^2 = 0.473$, $p < 0.001$), with a strong positive standardized coefficient ($\beta = 0.688$). Conversely, the negative attitude (GAIS negative) explained a small but statistically significant proportion of variance ($R^2 = 0.040$, $p = 0.008$), with a small negative effect ($\beta = -0.200$).

Discussion

The primary aim of this two-study investigation was to validate the Italian version of the General Attitudes towards Artificial Intelligence Scale (GAAIS). The findings support the hypothesis that the GAAIS is a valid and reliable measure of attitudes towards artificial intelligence within the Italian context.

Confirmatory factor analyses revealed a two-factor structure, consistent with the initial study [4], with the original validation [28] and with the subsequent studies replicated in other contexts (e.g [26]).,. The presence of a positive and a negative factor aligns with the notion that individuals may have mixed emotional responses to AI, oscillating between enthusiasm and concern, and specific negative emotion such as anxiety [40].

The results of Study 2 provide empirical support for the concurrent and predictive validity of the GAAIS scale. As hypothesized, positive attitudes towards artificial intelligence, as measured by the GAAIS positive factor, were positively correlated with general attitudes towards the use of AI, while the negative factor showed a significant negative correlation, confirming the concurrent validity.

Regarding predictive validity, the findings demonstrate that a positive attitude towards AI may influence the intention to use AI, with a strong trend, explaining approximately 47% of the variance. The standardized beta coefficient indicated a strong positive effect, highlighting the critical role of favorable perceptions in fostering engagement with AI technologies. In contrast, although the negative attitude factor also significantly predicted intention to use AI, its predictive power was markedly lower, accounting for only 4% of the variance, with a small negative effect.

This finding aligns with the existing literature [21], which highlights that a positive attitude towards a technology is a crucial antecedent of adoption intentions (e.g [22])., and is related to the theoretical frame of the Technology Acceptance Model [33]. Moreover, this study conducted with an Italian sample allowed us to take into account any emerging potential different results, due to cultural and contextual factors as has been indicated by recent research findings [30, 31, 43].

The findings of this research have important practical implications. First, the GAAIS can be used in future studies to investigate the factors influencing attitudes towards

Table 3 Comparison of regression models: positive and negative attitudes towards artificial intelligence as predictors of usage intention

Predictor	R	R^2	Adjusted R^2	F	p	β	Direction of Effect
GAAIS positive	0.688	0.473	0.470	157.358	< 0.001	0.688	Positive
GAAIS negative	0.200	0.040	0.034	7.286	0.008	−0.200	Negative

AI and to evaluate the impact of educational and informational interventions. Additionally, the scale can serve as a valuable measure for companies and organizations seeking to understand the perceptions of their employees and consumers regarding AI, to develop effective communication strategies and training. At a social level this tool could be useful within institutional national programs that are working in the strategic direction of the digital competencies gap reduction, by integrating a socio-psychological perspective.

Despite the promising results and applications, it is important to acknowledge some limitations of the study. Although the two studies were conducted with 2 heterogeneous and different subsamples, these may not be fully representative of the wide set of characteristics of the Italian population. Furthermore, the study is focused on general attitudes towards AI, without delving deeply into perceptions related to specific AI applications which could be characterized differently depending on factors like familiarity to use, specific AI applications reputation, etc. Further studies then may compare the attitude towards different AI tools and analyse the role of such other variables, at an individual and or social level, functioning as predictors as mediators and or moderators. Predictive validity was assessed through a cross-sectional rather than a longitudinal study and or including behavioral measures and experimental design, as well as deeper qualitative data future research developments may include these methodological issues too.

There are few strictly methodological considerations that deserve attention concerning the factor structure of the GAAIS and then its construct validity. The two-dimensional structure that emerged from our analyses corresponds to items that are worded in positive and negative directions respectively, raising the possibility that these factors might reflect method effects related to item wording rather than substantive content dimensions. Although our study supports the substantive nature of these factors - including their differential relationships with usage intentions and their distinct patterns of correlation with attitudes towards AI use (positive versus negative correlations) - further research is needed to definitively establish their construct validity. In particular, the cultural invariance testing procedures [58–60] may be used to strengthen the comparability of the Italian adaptation with the original and the other international GAAIS versions towards a cross-cultural direction. Moreover, examining the factors' relationships with a broader range of theoretically relevant variables would help establish their discriminant validity. Such validation efforts would help ensure that the two-factor structure genuinely reflects meaningful psychological dimensions rather than artifacts of measurement methodology.

Future research could delve deeper into the analysis of attitudes towards AI, exploring the specific relationship between people's AI usage behavior, digital literacy and AI attitudes. This, in line with the main research frames and developments on this topic, could extend the body of knowledge to address the strong demand for the enhancement of people's digital competencies in this "New Technological Era" in Italy as throughout the country's contexts.

Moreover, new investigations may deepen the GAAI study in various population groups (e.g., young, elderly, professional categories, individuals with different educational backgrounds, values) of the Italian actual population, to enlarge the generalizability of this study and to provide new findings taking into account the specific role of the socio-cultural variables [19, 20, 26, 30, 40, 43]. Additionally, it would be interesting to evaluate the interplay among individual traits, personal experiences, emotional and wellbeing factors during AI use, situational factors and acceptance measures of AI to better understand the role of these variables on attitude towards AI [61, 62]. Also, future research should focus on developing novel theoretical frameworks specifically designed for AI acceptance, moving beyond traditional technology acceptance models like TAM. While established models have provided valuable insights, the unique characteristics of AI technologies - such as autonomy, learning capabilities, and potential job displacement - demand more specialized theoretical approaches. Current evidence suggests that traditional acceptance models may not fully capture the complexity of AI acceptance, as demonstrated by inconsistent findings across studies (e.g [19, 21]).,. The role of other variables such as trust, as a relevant multidimensional variable, in the development of models on the acceptance of AI technologies has been confirmed too (e.g [27, 28, 63].,. New future models should incorporate, then, additional factors that are particularly relevant to AI, such as perceived threat of job loss, trust in AI decision-making, ethical concerns, and the need for human-AI collaboration.

Conclusion

The study allowed us to analyze the attitudes towards Artificial Intelligence, a relevant topic in the current scientific research, more specifically this research provides the Italian version of the GAAIS as a tool for measuring attitudes towards artificial intelligence. The scale, in the adapted version, has demonstrated reliability and validity and can be employed and developed in a wide range of research contexts. Moreover, the study confirms the already known relationship between attitudes and intention to use technologies even regarding AI use. However, despite these positive first results, further research is needed to replicate these findings, also with different research designs, to investigate additional variables to test other aspects of validity. As a general conclusion this scale could be a proper tool for future research interested in developing the theoretical frameworks on this topic, aimed to enhance our understanding of attitudes towards AI, as well as to develop effective interventions to promote informed and critical acceptance of this technology.

Abbreviations

AIC	Akaike's Information Criterion
α	Cronbach's Alpha
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
GAAIS	General Attitudes towards Artificial Intelligence Scale
RMSEA	Root Mean Square Error of Approximation
SRMR	Standardized Root-Mean-Square Residual
TAM	Technology Acceptance Model
χ2	chi-square
ω	McDonald's Omega coefficient

Supplementary Information

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Supplementary Material 1

Supplementary Material 2

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Author contributions
Each author has made substantial contributions to complete the study and the manuscript as follows: L. C.: Conceptualization, Methodology design, data acquisition and interpretation, Writing– review & editing, Supervision; A.R.: Data acquisition, Writing– review & editing; G.D.S.: Writing– review & editing; A.Z.: Conceptual and Methodology design, Formal Analysis, Writing, review & editing.

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Data availability
The datasets analysed during the current study are available in the Open Science Framework (OSF) repository webpage https://osf.io/6ex2h/?view_only=5ab73fa315824e20836a459f4ea7b8a2.

Declarations

Ethics approval and consent to participate
Participants voluntarily participated in the research, filling out an online protocol. In the presentation of the research, it was asked to express informed consent to the anonymous processing of data. All participants marked their consent after reading the form and only after they started to fill out the research protocol. This research complied with the ethical rules of the Italian Association of Psychology (AIP). The study was granted ethical clearance by the Internal Ethic Review Board of Psychology Research– IERB of the Department of Educational Sciences, Section of Psychology - University of Catania on 03/06/2024 (approval number: Ierb-Edunict-2024.06.03/07).

Consent for publication
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Competing interests
The authors declare no competing interests.

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