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Validation of the general attitudes towards Artificial Intelligence Scale in the Italian context and the role of trust

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ABSTRACT

Recent advancements in Artificial Intelligence (AI) have profoundly impacted various sectors, including healthcare, education, and security, leading to a paradigm shift in the way in which society engages with technology. Considering the increasing integration of AI in these critical areas, it is important to understand people's attitudes towards this technology to understand their acceptance of AI. The present study aimed to validate the General Attitudes towards Artificial Intelligence Scale (GAAIS) in the Italian context. The study examined the psychometric properties of the scale and explored the relationship between interpersonal trust and attitudes towards AI. The GAAIS, previously validated in the UK and Turkey, was translated into Italian. The scale was administered to two independent samples of Italian adults (Study 1, N = 205; Study 2, N = 121). Participants varied in age, gender, and self-reported familiarity with AI, offering a culturally specific perspective on attitudes toward AI in the Italian context. The study also investigated potential factors that may influence AI attitudes, including demographic characteristics, computer usage, and knowledge about AI. The findings supported the hypothesized link between positive attitudes with younger male individuals, higher education levels and greater familiarity with AI. Data also showed that epistemic mistrust –i.e. the lack of confidence in the reliability of a source measured through the Epistemic Trust, Mistrust and Credulity Questionnaire (ETMCQ), correlated with skepticism, while epistemic trust –i.e. the willingness to accept information from others as reliable– was linked to forgiving attitudes towards AI drawbacks. These findings underscored the pivotal role that interpersonal trust and cultural context play in shaping public attitudes towards AI.

1. Introduction

Advances in Artificial Intelligence (AI) are affecting many areas of daily life, influencing diverse fields, such as healthcare, education and security. As AI becomes increasingly embedded in sensitive areas, understanding public attitudes towards this technology becomes critical. Public perception of AI is crucial to determining whether it could be accepted in strategic and sensitive contexts. In healthcare, AI technology is revolutionizing diagnosis, treatment planning and patient monitoring. For example, AI-powered tools are being used in the early detection of cancer, with the use of imaging to identify subtle abnormalities that may elude human specialists (Hunter et al., 2022; Moore et al., 2017). Similarly, AI enabled electronic health records are improving data management and enabling more efficient and personalized care (Nova, 2023). However, the adoption of AI in the health care sector raises critical questions about reliability, accountability and patient safety, highlighting the need for trust in AI systems in such high-stakes environments. In education, AI has led to a reinvention of teaching and learning processes by providing personalized learning experiences, automated assessment tools, and even social robots that support classroom interaction and emotional engagement (Kandlhofer et al., 2016; Sacco et al., 2023). While these innovations promise to improve learning

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outcomes, their integration in the classroom is also heavily dependent on trust – e.g., confidence in these technologies to complement human educators, and to maintain educational equity. In these contexts, the role of AI has a direct impact on human lives and societal well-being, and the importance of trust becomes clear. Without trust in AI systems - whether in their reliability, fairness or intentions - users may resist adoption, limiting the transformative potential of these technologies. On the other hand, credulity can result in overdependence on AI, increasing the risk of harm due to technological limitations or misuse.

1.1. Attitudes towards AI

As can be seen from the examples above, the widespread use of AI urgently requires an understanding of the attitudes of people towards this technology and the development of instruments that can provide information on people's attitudes, which can help guide how people choose to adopt and use AI. One tool designed to measure attitudes towards AI is the General Attitudes towards Artificial Intelligence Scale (GAAIS), developed by Schepman and Rodway (2020, 2023). The GAAIS is a multifaceted instrument that assesses both positive and negative attitudes towards AI, thereby capturing the polarized views that are frequently observed in public discourse. These views range from optimism about its transformative potential to fear of its risks and unintended consequences. This polarization is reflected in its bi-factorial structure, which has been validated across different cultural contexts, including the United Kingdom and Turkey (Schepman & Rodway, 2020; Kaya et al., 2024). Previous research employing the GAAIS has highlighted several factors influencing attitudes toward AI. Among demographic variables, gender differences are observed, with males generally expressing more positive attitudes than females (Schepman & Rodway, 2023; Zhang & Dafoe, 2019). Women, for instance, tend to show more hesitation toward AI (Park et al., 2022). Regarding age, while some studies suggest older individuals might adopt favorable attitudes to avoid feeling outdated (Park et al., 2022), others indicate a more positive outlook among younger demographics (Schepman & Rodway, 2023). Beyond demographics, familiarity with technology, often reflected in computer use and AI knowledge, consistently correlates with more optimistic views. Individuals with computer science experience or self-reported digital skills are more likely to support and adopt AI (Vu & Lim, 2022; Zhang & Dafoe, 2019). Specifically, greater AI knowledge appears to enhance trust, leading to more positive attitudes as individuals better understand its practical applications, whereas limited exposure can foster skepticism (Belanche et al., 2019; Mantello, Ghotbi, Ho, & Mizutani, 2024). This suggests that advanced AI knowledge, or frequent computer use, generally leads to more positive attitudes and greater tolerance for AI's limitations (Schepman & Rodway, 2023; Kaya et al., 2024).

This nuanced understanding of individual attitudes, encompassing both positive and negative facets, is further reflected in the broader societal conceptualization of AI. This mirrors the pervasive attitudes in societies, where a pronounced dichotomy exists between those who hold exceedingly positive views and those who harbor catastrophic fears regarding AI (Crawford, 2021). This could be also affected by the perception of such technology, given by movies or books (both fictional and non-fictional) from others that give a negative image of AI, affecting people's attitudes towards AI negatively (Siau & Wang, 2018). This represents a global trend. In fact, a first cross-cultural validation of the GAAIS has already been carried out with a Turkish sample (Kaya et al., 2024). This study demonstrated the optimist/catastrophist conceptualization by reconfirming the bi-factorial structure of the GAAIS validated in UK. Other constructs such as personality traits, knowledge of AI and use of personal computers were also examined in the Turkish validation. The findings suggest that the Big Five personality traits, particularly agreeableness, play a role in shaping attitudes toward AI, with agreeableness positively influencing tolerance for AI drawbacks. While openness and emotional stability were initial predictors in the Turkish sample, AI-specific factors like anxiety and fear were more influential, highlighting the interplay between personality, knowledge, and situational factors in attitudes toward AI systems.

1.2. The role of trust in AI

Trust has been extensively examined in automated technologies (Muir & Moray, 1996). To trust AI systems, individuals must have confidence that the technology will operate safely and reliably. This becomes especially critical in fields such as medicine, cybersecurity, and education, where the risks are particularly high. Beyond the technical aspects, trust in AI is also shaped by more complex, social factors. One of the most significant concerns stems from the fact that AI applications are often managed by large corporations, which collect vast amounts of user data to enhance their AI systems and drive profitability. Corporate distrust strongly predicts negative attitudes toward AI, impacting both its perceived drawbacks and benefits. High distrust correlates with skepticism toward AI, potentially driven by ethical concerns surrounding data collection practices and the lack of informed user consent (Schepman & Rodway, 2023). These issues, as highlighted by Schepman and Rodway (2023), underscore the need for corporate transparency and ethical engagement to foster trust and acceptance of AI systems, benefiting both users and companies.

The concepts of epistemic trust, mistrust and credulity are directly relevant to trust in AI. Trust in AI consists of considering it as a reliable and transparent tool, avoiding the skepticism that hinders its adoption (i.e. mistrust) or the blind reliance that risks exploitation or misuse (i.e. credulity). Striking this balance is key to fostering effective and responsible AI integration. Despite significant advances in AI research, the role of individual trust in shaping attitudes toward AI remains underexplored. Campbell et al. (2021) identified three key psychological dimensions of trust in humans—epistemic trust, mistrust, and credulity—that are closely linked to attitudes toward AI. Specifically, epistemic trust denotes the propensity to accept knowledge imparted by others as both reliable and pertinent (Sperber et al., 2010; Fonagy et al., 2015). It facilitates the navigation of complex information and the adoption of new technologies, including AI. Conversely, epistemic distrust is characterized by a lack of confidence in the reliability of knowledge sources, which can hinder engagement with AI systems or amplify concerns about their potential risks. Epistemic credulity, defined as an unquestioning acceptance of information, has the potential to amplify susceptibility to misinformation and exaggerated fears about AI. These individual trust dimensions are of particular relevance in the context of AI, where technologies frequently function as intermediaries of knowledge. It is of the essence to recognize that trust in these systems is pivotal, particularly in domains such as medicine and education, where decisions guided by AI bear significant consequences for human health, learning, and safety. A deeper understanding of how epistemic trust, mistrust, and credulity shape attitudes toward AI can provide crucial insights into the psychological foundations of technology acceptance. Furthermore, examining these dynamics within the Italian context offers a culturally nuanced perspective that complements existing research, particularly as AI continues to expand its presence across diverse sectors and becomes a focal point of public and academic discourse.

2. Aims and research hypothesis

The present study aimed to validate the GAAIS in the Italian context and to investigate individual differences in attitudes toward AI. This validation expands the actual understanding of how Italians perceive AI technologies, which are increasingly prevalent across various sectors, such as work, education, and healthcare. Additionally, AI is a topic of growing interest in both scientific discourse and popular media, making it essential to assess public attitudes toward this transformative technology.

Building upon prior research, our study examines key factors influencing AI acceptance, which include demographic variables such as gender, age, and education, often associated with shaping general attitudes toward AI (Schepman & Rodway, 2023; Kaya et al., 2024). We also consider familiarity with technology, specifically computer use and AI knowledge, which has been linked to more optimistic evaluations and greater tolerance of AI limitations (Belanche et al., 2019; Zhang & Dafoe, 2019). In addition to these individual characteristics, recent psychological research emphasizes the significance of epistemic trust in influencing individuals' interaction with novel and intricate information systems. According to Campbell et al. (2021), epistemic trust (i.e. the willingness to consider communicated knowledge as reliable), mistrust (i.e. a tendency to reject information), and credulity (i.e. uncritical acceptance of information) represent core dimensions of trust. These constructs may influence how individuals relate to AI, especially in contexts where technology acts as a mediator of information and decision-making.

Based on this framework, we formulated three main hypotheses to test the role of demographic characteristics, technology familiarity, and epistemic trust in shaping attitudes toward AI. The overall methodological and analytical workflow is summarized in Fig. 1.

Hypothesis 1. We aimed to investigate which demographic characteristics (age, gender, education, employment status) predict people's attitudes toward AI. We hypothesized that males (H1a), younger individuals (H1b), those with higher levels of education (H1c), would exhibit more positive attitudes toward AI and be more forgiving of its negative aspects.

Hypothesis 2. We hypothesized that computer usage and knowledge of AI would be positively associated with people's attitudes toward AI. Specifically, we expected that greater computer use (H2a) and higher AI knowledge (H2b) would be linked to more positive attitudes and greater tolerance for AI's limitations.

Hypothesis 3. We aimed to examine the relationship between epistemic trust and attitudes toward AI. Specifically, we hypothesized that people with high levels of epistemic trust (H3a) would adopt more positive attitudes toward AI. Conversely, individuals with high levels of epistemic mistrust (H3b) will display more negative attitudes, as mistrust is linked to skepticism about the reliability of information sources, including AI. Since epistemic trust pertains specifically to the acceptance of communicated knowledge, its role in shaping AI attitudes is particularly relevant. Additionally, we expect that individuals with high epistemic credulity (H3c) may also show negative attitudes, as uncritical acceptance of information can increase susceptibility to misinformation and amplify fears about AI.

3. Methods

3.1. Materials

3.1.1. Demographic

The socio-demographic measures were adapted from Kaya et al. (2024). These questions assessed participants age, gender, education level, and employment status, along with their self-reported level of AI knowledge and computer proficiency. AI knowledge was measured on a four-point scale, ranging from 1 ("I have no knowledge at all") to 4 ("I have detailed knowledge"). Similarly, computer proficiency was assessed on a four-point scale, from 1 ("I can barely use the computer") to 4 ("I am an expert computer user").

3.1.2. GAAIS

GAAIS was developed by Schepman and Rodway (2020) and comprises 20 items. These items are divided into two distinct factors, reflecting positive and negative attitudes toward AI. The positive factor (GAAIS-P) captures favorable perspectives on AI, such as its potential benefits, efficiency, and capability to improve daily life. Example items include "I am impressed by what artificial intelligence can do" and "Artificial intelligence can have positive impacts on people's wellbeing." In contrast, the negative factor (GAAIS-N) encompasses concerns and apprehensions about AI, such as its potential misuse, ethical implications, and risks to personal security. Example items include "Artificial intelligence might take control of people" and "I find artificial intelligence sinister." The items are assessed on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The GAAIS items were back-translated following standard guidelines (Herdman et al., 1998; Beaton et al., 2000; Wild et al., 2005; see Appendices A and B). Three bilingual experts collaboratively translated the scale into Italian, and

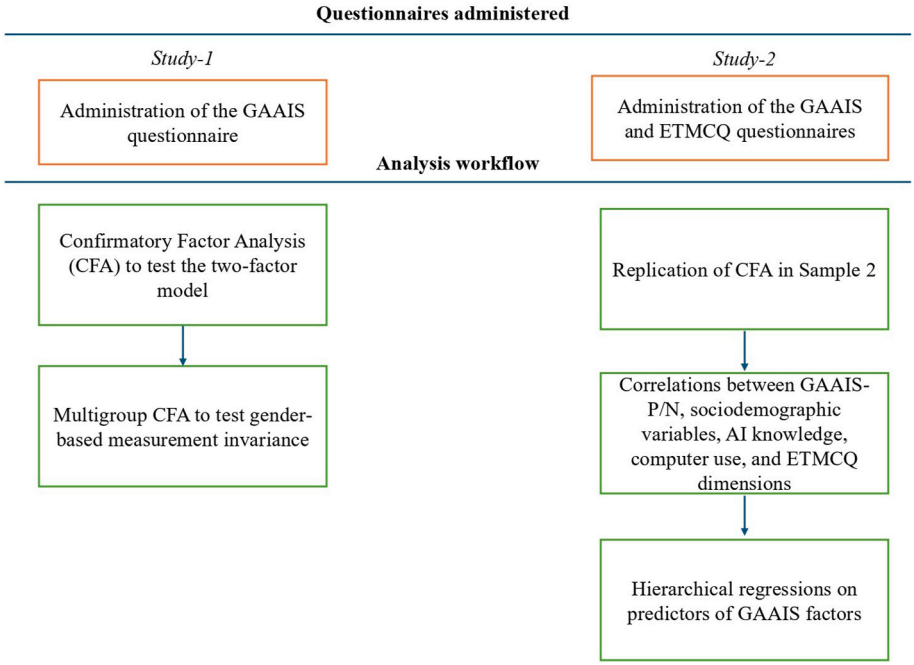

Fig. 1. Overview of the methodological and analytical workflow across Study 1 and Study 2.

another expert back-translated it into English. The back-translation was reviewed for consistency with the original, and any discrepancies, mainly involving synonyms, were resolved through discussion. The first author supervised the entire process to ensure accuracy.

3.1.3. Epistemic trust, mistrust, and Credulity Questionnaire (ETMCQ)

The Epistemic Trust, Mistrust and Credulity Questionnaire (ETMCQ) (Campbell et al., 2021) consists of 15 items with a seven-point Likert scale (1 = not true, 7 = very true) and measures the degree of Epistemic Trust (ET; items 1, 2, 7, 8, 13), Epistemic Mistrust (EM; items 3, 4, 9, 10, 14, 15) and Epistemic Credulity (EC; items 5, 6, 12). The Italian validation was validated by Liotti and colleagues (2023).

4. Study 1: Attitudes towards AI - Confirmatory validation of the GAAIS

The aim of Study 1 was to confirm the original two factors structure of the GAAIS (Schepman & Rodway, 2020) with a Confirmatory Factor Analysis.

4.1. Sample

The study involved 205 native Italian speakers: 105 males and 100 females, with a mean age of 36.55 years (SD = 11.8, range 18–65), 36.0 (SD = 10.9) for males and 37.6 (SD = 12.6) for females., following the guidelines suggested by Austin and Steyerberg (2015), which recommend a minimum of 10 participants per item for factorial analyses. The Prolific platform was used to recruit participants. Participants were paid 9£/h, following the guidelines established by Prolific. The local Ethics Committee of the Department of Psychology at Università Cattolica del Sacro Cuore in Milan granted ethical approval for the experimental protocols of all studies conducted as part of this research. For a detailed overview of the final sample's sociodemographic backgrounds, including education levels, occupational status, self-reported computer use, and AI knowledge, please refer to Table 1.

4.2. Procedure

The online questionnaire was conducted using the Qualtrics platform, which provided a user-friendly interface for participants. Before accessing the questionnaire, participants were required to provide their informed consent, ensuring they understood the study's purpose and their rights. Once consent was obtained, participants completed the GAAIS. The items were displayed one at a time in a randomized order to minimize response bias. To ensure that participants were engaged and had carefully read the questions, an attention check was included within the survey following Schepman and Rodway (2020).

Table 1
Sociodemographic characteristics of the two samples.

Sociodemographic characteristics	Sample 1	Sample 2
	N = 205	N = 121
Age mean ± SD	36.55 ± 11.8	36.57 ± 11.48
Gender	%	%
Male	51.22 %	50.41 %
Female	48.78 %	49.59 %
Education level	%	%
Elementary school	0.5 %	0 %
Middle school	0.5 %	0.8 %
High school	44.8 %	39.6 %
University	42.9 %	44.6 %
Postgraduate	11.2 %	14.8 %
Employment status	%	%
Employed	71.7 %	74.3 %
Unemployed	22.4 %	21.4 %
Stay-at-home	4.3 %	3.3 %
Retired	1.4 %	0.8 %
Computer use	%	%
Beginner	0.9 %	0.8 %
Intermediate	45.8 %	45.4 %
Advanced	53.1 %	53.7 %
AI Knowledge	%	%
None	2.4 %	2.4 %
Basic	44.8 %	41.3 %
Moderate	42.4 %	42.9 %
Advanced	10.2 %	9 %

4.3. Results Study 1

4.3.1. Confirmatory Factor Analysis

A Confirmatory Factor Analysis was performed in JASP (JASP Team, 2020) to validate the two-factor structure of the GAAIS, previously identified in the original validation (Schepman & Rodway, 2020, 2023). The DWLS (diagonally weighted least squares) estimator was chosen because the data at the item level were ordinal (Li, 2016). The CFA was performed on a two-factor model. First, Bartlett's test of sphericity was checked to confirm inter-item correlations ($\chi^2 = 1893.617$, $df = 190$, $p = 0.001$), and the Kaiser-Meyer-Olkin (KMO = 0.925) was used to assess sampling adequacy. The two-factor model demonstrated a good fit with the data ($\chi^2/df = 2.082$; CFI = 0.898; TLI = 0.885; SRMR = 0.063; RMSEA = 0.073, [CI] = 0.062–0.083). However, item no. 13 ("An artificially intelligent agent would be better than an employee in many routine jobs") had a suboptimal R^2 value (0.19), indicating that its variance was poorly captured by the common factor. However, as the fit indices were already very good by keeping this item, we decided not to remove it. Although most fit indices met the recommended cut-off values (SRMR = 0.063; RMSEA = 0.073), there was space for improvement. An inspection of modification indices (MI > 10) suggested that correlations between the error terms of certain item pairs should be included in the model. Items 13 and 16 (MI = 24.830), 1 and 13 (MI = 25.301), 3 and 6 (MI = 19.797), 5 and 12 (MI = 13.707), 7 and 18 (MI = 10.289) and 12 and 18 (MI = 10.750) correlated. After making these adjustments, the CFA was re-run, and the goodness-of-fit indices indicated a satisfactory fit for the two-factor model (see Table 2). Factor loadings are shown in Table 3. Cronbach's α indicated high internal consistency, with values of 0.893 for the GAAIS-P and 0.839 for the GAAIS-N.

We conducted a multigroup CFA to assess the model across gender. To ensure inter-item correlation, we checked Bartlett's sphericity test ($\chi^2 = 964.841$, $df = 190$, $p = 0.001$ for males; $\chi^2 = 1050.120$, $df = 190$, $p = 0.001$ for females) and confirmed sample adequacy using the Kaiser-Meyer-Olkin measure (KMO = 0.872 for males; KMO = 0.910 for females). The two-factor model showed a good fit to the data ($\chi^2/df = 1.693$; CFI = 0.871; TLI = 0.855; SRMR = 0.078; RMSEA = 0.082; [CI] = 0.071–0.094). However, for males, items 6 ($R^2 = 0.17$), 13 ($R^2 = 0.15$), and 16 ($R^2 = 0.14$) had suboptimal R^2 values, indicating that their variances were not well explained by the common factor. While most fit indices were within the recommended range (SRMR = 0.078; RMSEA = 0.082), the model could still be refined. Modification indices (MI > 10) suggested that adding correlations between error terms for certain item pairs would improve the model. The items that correlated were items 13

Table 2
Study 1 goodness-of-fit indices generated by Confirmatory Factor Analysis (CFA) with and without modification indices.

	Recommended value	Value obtained without MI	Value obtained with MI
X^2/df	≤3.00	2.082	1.499
CFI	≥0.90	0.898	0.954
TLI	≥0.90	0.885	0.947
SRMR	≤0.08	0.063	0.054
RMSEA	≤0.08	0.073([CI] = 0.062–0.083)	0.049 ([CI] = 0.036–0.062)

Table 3
Factor loadings Study 1.

						95 % Confidence Interval			
Factor	**Indicator**	**Estimate**	**Std. Error**	**z-value**	**p**	**Lower**	**Upper**	**Mean**	**Std. Deviation**
GAAIS_POSITIVE									
	GAAIS_1	0.524	0.071	7.325	<0.001	0.384	0.664	2.854	1.056
	GAAIS_2	0.719	0.063	11.476	<0.001	0.596	0.842	3.634	1.009
	GAAIS_4	0.704	0.068	10.390	<0.001	0.571	0.837	2.917	1.065
	GAAIS_5	0.457	0.053	8.633	<0.001	0.353	0.561	4.156	0.801
	GAAIS_7	0.854	0.060	14.150	<0.001	0.736	0.972	3.717	1.038
	GAAIS_11	0.681	0.050	13.710	<0.001	0.584	0.779	3.737	0.845
	GAAIS_12	0.649	0.052	12.354	<0.001	0.546	0.751	3.712	0.863
	GAAIS_13	0.495	0.079	6.304	<0.001	0.341	0.649	3.102	1.139
	GAAIS_14	0.444	0.040	11.229	<0.001	0.367	0.522	4.210	0.634
	GAAIS_16	0.502	0.069	7.254	<0.001	0.366	0.637	3.380	1.020
	GAAIS_17	0.725	0.070	10.295	<0.001	0.587	0.863	3.390	1.104
	GAAIS_18	0.810	0.071	11.372	<0.001	0.670	0.949	3.541	1.144
GAAIS_NEGATIVE									
	GAAIS_3	0.483	0.064	7.560	<0.001	0.358	0.608	2.702	0.926
	GAAIS_6	0.447	0.067	6.718	<0.001	0.317	0.578	2.707	0.951
	GAAIS_8	0.827	0.064	12.929	<0.001	0.702	0.953	3.454	1.050
	GAAIS_9	0.610	0.076	8.015	<0.001	0.461	0.760	3.541	1.118
	GAAIS_10	0.792	0.063	12.483	<0.001	0.668	0.916	2.980	1.029
	GAAIS_15	0.885	0.076	11.647	<0.001	0.736	1.034	3.112	1.209
	GAAIS_19	0.719	0.076	9.444	<0.001	0.570	0.869	3.507	1.149
	GAAIS_20	0.585	0.074	7.872	<0.001	0.440	0.731	3.298	1.087

and 16 (MI = 21.852), 5 and 12 (MI = 13.041), 16 and 9 (MI = 10.278), 1 and 13 (MI = 17.295), 3 and 6 (MI = 12.910) and 7 and 3 (MI = 12.632). After incorporating these adjustments and re-running the CFA, the fit indices confirmed a satisfactory fit for the two-factor model (see Table 4).

To ensure that the suboptimal items did not significantly affect the already strong fit indices, we re-run the CFA excluding the items 6, 13, and 16. Bartlett's sphericity test was checked to confirm inter-item correlations (χ^2 = 813.095, *df* = 136, *p* = 0.001 for males; χ^2 = 895.095, *df* = 136, *p* = 0.001 for females), and the Kaiser-Meyer-Olkin (KMO = 0.892 for males; KMO = 0.920 for females) indicated sample adequacy. The revised two-factor model showed a good fit to the data (χ^2/df = 1.482; CFI = 0.928; TLI = 0.917; SRMR = 0.069; RMSEA = 0.069; [CI] = 0.053–0.083). An analysis of modification indices (MI > 10) suggested that adding correlations between error terms of certain item pairs could further improve the model. The items 5 and 12 (MI = 13.061) and 7 and 3 (MI = 11.961) correlated. After these adjustments and re-running the CFA, the fit indices confirmed that the two-factor model provided a satisfactory fit (see Table 5). Despite the model's improved fit, though the changes were not substantially significant, we decided to retain the all the items. Cronbach's α indicated that, if item 6 was dropped, it changed from 0.893 to 0.834; similarly, removing item 13 led to the same value of 0.893, and item 16 to 0.890. Since the modifications are not substantial, this further supports retaining all the items.

Table 4
Study 1 goodness-of-fit indices generated by multigroup Confirmatory Factor Analysis (CFA) across gender with and without modification indices.

	Recommended value	Value obtained without MI	Value obtained with MI
X^2/df	≤3.00	1.693	1.393
CFI	≥0.90	0.871	0.929
TLI	≥0.90	0.855	0.918
SRMR	≤0.08	0.078	0.070
RMSEA	≤0.08	0.082([CI] = 0.071–0.094)	0.062 ([CI] = 0.048–0.075)

Table 5
Study 1 goodness-of-fit indices generated by multigroup Confirmatory Factor Analysis (CFA) across gender with and without modification indices without items number 6, 13 and 16.

	Recommended value	Value obtained without MI without items 6, 13 and 16	Value obtained with MI without items 6, 13 and 16
X^2/df	≤3.00	1.482	1.376
CFI	≥0.90	0.928	0.944
TLI	≥0.90	0.917	0.935
SRMR	≤0.08	0.069	0.067
RMSEA	≤0.08	0.069([CI] = 0.053–0.083)	0.061([CI] = 0.043–0.076)

5. Study 2: Prediction of GAAIS from epistemic Trust, Mistrust and Credulity measures (ETMCQ)

Study 2 aimed to investigate the hypothesis concerning the prediction of the GAAIS alongside interpersonal trust measures. Specifically, this study examined the constructs of epistemic trust, mistrust, and credulity. The objective was to explore how these dimensions influence participants' attitudes toward AI. By analyzing the relationships between these variables, the study sought to gain deeper insights into the factors that shape individuals' perceptions of AI and the extent to which trust influences these attitudes.

5.1. Sample

121 native Italian speakers participated in Study 2: 61 males and 60 females. The mean age was 36.57 (SD = 11.48, age range = 18–65 years) for the total sample, 36.63 for males (SD = 11.12), and 36.51 for females (SD = 11.92). This study followed the same guidelines as in Study 1. The local Ethics Committee of the Department of Psychology at Università Cattolica del Sacro Cuore in Milan granted ethical approval for the experimental protocols of all studies conducted as part of this research.

The final sample included adults from diverse socio-demographic backgrounds. The sociodemographic composition of the final sample, detailing aspects like education levels, occupational status, computer use, and AI knowledge, is presented in Table 1.

5.2. Procedure

The second study started with the administration of the GAAIS, following the same procedure and the validated structure of Study 1. Afterwards, the ETMCQ was presented. In the ETMCQ, items were shown one at a time in a randomized order, and an additional attention check was included to verify participants' engagement with the questionnaire. Consistent with the first study, participants in Study 2 received the monetary reward as required by the payment guidelines established by Prolific.

5.3. Results Study 2

5.3.1. Confirmatory Factor Analysis

To enhance the robustness of our results, we also performed a CFA on the second sample. Once again, the CFA was conducted on a two-factor model. Bartlett's test of sphericity was used to confirm inter-item correlations ($\chi^2 = 1052.347$, $df = 190$, $p = 0.001$), and sample adequacy was verified using the Kaiser-Meyer-Olkin measure (KMO = 0.877). The two-factor solution showed a good fit to the data (χ^2/df = 1.657; CFI = 0.882; TLI = 0.867; SRMR = 0.084; RMSEA = 0.074, [CI] = 0.058–0.089). However, the R^2 values for items 1 ($R^2 = 0.19$), item 16 ($R^2 = 0.10$), and item 20 ($R^2 = 0.17$) were below optimal, indicating that these items were poorly explained by the common factor. However, given that we were conducting an additional robustness check of the factor structure and considering the strong fit indices, we decided to do not exclude these items. While most fit indices met the recommended thresholds (SRMR = 0.084; RMSEA = 0.074), further improvement was suggested by modification indices (MI > 10), which indicated that correlations between the error terms of some item pairs should be included. Items 1 and 5 (MI = 11.240) correlated. After making these adjustments and re-running the CFA, the goodness-of-fit indices confirmed a satisfactory fit for the two-factor model (see Table 6). Factor loadings are shown in Table 7. Cronbach's α indicated high internal consistency, with values of 0.883 for the GAAIS-P and 0.801 for the GAAIS-N.

We conducted a multigroup CFA to examine the model across gender. Bartlett's sphericity test was used to confirm inter-item correlations ($\chi^2 = 568.333$, df = 190, p = 0.001 for males; $\chi^2 = 598.325$, df = 190, p = 0.001 for females), and sample adequacy was evaluated using the Kaiser-Meyer-Olkin measure (KMO = 0.773 for males; KMO = 0.807 for females). The model showed a reasonable fit to the data (χ^2/df = 1.513; CFI = 0.823; TLI = 0.800; SRMR = 0.101; RMSEA = 0.092, [CI] = 0.075–0.108). However, the R^2 values were suboptimal for certain items, indicating that their variances were not well explained by the common factor. Specifically, items 1 ($R^2 = 0.102$) and 6 ($R^2 = 0.081$) for males, and items 16 ($R^2 = 0.099$), 9 ($R^2 = 0.158$), and 20 ($R^2 = 0.129$) for females had low R^2 values. Despite this, we chose to retain these items. Although most fit indices met the recommended cut-offs (SRMR = 0.101; RMSEA = 0.092), the model could still be refined. An examination of modification indices (M I > 10) suggested that incorporating correlations between certain item error terms could improve the model. Items 1 and 13 (MI = 11.850) and 11 and 14 (MI = 10.448) correlated. After re-running the CFA with these modifications, the fit of most indices confirmed a satisfactory fit for the two-factor model (see Table 8). Although not all indices are optimal, the robustness of the indices, combined with the smaller sample size, suggests that the confirmation on the second sample remains valid. Cronbach's α for the multigroup analysis indicated high internal consistency, with values of 0.865 for the GAAIS-P and 0.772 for the GAAIS-N.

Table 6
Study 2 goodness-of-fit indices generated by Confirmatory Factor Analysis (CFA) with and without modification indices.

	Recommended value	Value obtained without MI	Value obtained with MI
X^2/df	≤3.00	1.657	1.595
CFI	≥0.90	0.882	0.894
TLI	≥0.90	0.867	0.880
SRMR	≤0.08	0.084	0.083
RMSEA	≤0.08	0.074 ([CI] = 0.058–0.089)	0.070 ([CI] = 0.054–0.086)

5.3.2. Correlations

We performed correlation analysis. Descriptive statistics and Pearson correlation analysis was carried out (see Table 9). First, there was a significant positive correlation ($r = 0.404$, $p < 0.001$) between AI knowledge and GAAIS-P. This indicates that individuals who have stronger knowledge about AI tend to adopt a more positive attitude towards it. Additionally, there was a significant negative correlation ($r = -0.280$, $p < 0.001$) between GAAIS-P and gender, indicating that females tend to have more concerns or skepticism about AI. Finally, there was a significant negative correlation ($r = -0.303$, $p < 0.001$) between GAAIS-N and epistemic mistrust (ETMCQ-EM).

Lastly, we performed a correlation between the GAAIS-P and the GAAIS-N factors. The correlation analysis revealed a positive relation between the two dimensions of the GAAIS ($r = 0.472$, $p < 0.001$). It is important to note that the GAAIS-N scale was reverse-scored, such that higher scores reflect less negative attitudes toward AI.

5.3.3. Regressions: predicting the GAAIS-P

A hierarchical multiple linear regression was carried out to explore how gender, age, education, employment status, computer use, AI knowledge, and the ETMCQ subscales (ET, EM, EC) predict positive attitudes toward AI (see Table 10). In the first model, with age and gender as predictors, the analysis showed that the gender significantly contributed to explaining GAAIS-P [R^2 change = 0.079, F change (2, 119) = 5.088, p = 0.008] (see Model I in Table 10). In the second model, additional factors (education level, computer use, AI knowledge, and employment status) were introduced (see Model II). These new variables explained an additional 12 % of the variance in GAAIS-P [R^2 change = 0.116, F change (4, 115) = 4.134, $p = 0.04$], with AI knowledge emerging as the only significant predictor of GAAIS-P ($\beta = 0.389$, $p < 0.001$). Finally, in Model III, the ETMCQ subscales (ET, EM, EC) were added. This inclusion explained an additional 3 % of the variance in positive attitudes toward AI [R^2 change = 0.033, F change (3, 112) = 1.619, $p = 0.189$], though it was not statistically significant. AI knowledge remained the only significant predictor, strengthening its predictive power ($\beta = 0.418$, $p < 0.001$).

5.3.4. Regressions: predicting the GAAIS-N

A separate hierarchical multiple linear regression analysis was conducted to examine the predictive effects of gender, age, education, employment status, level of computer use and level of knowledge of AI, and ETMCQ subscales (ET, EM, EC) on GAAIS-N (see Table 11). In this second regression model, the focus was on identifying predictors of negative attitudes toward AI. In the first two models there were no significant effects, while EM was a significant predictor in the third model [R^2 change = 0.118, F change (3, 112) = 5.151, p = 0.002, ($\beta = -0.293$, p = 0.002], indicating that individuals with higher epistemic mistrust—i.e., those who tended to distrust information or new knowledge—were less likely to have forgiving attitudes towards AI drawbacks, which is what the (reverse-scored) GAAIS-N measures.

6. Discussion

6.1. Psychometric validation of the GAAIS

The present study aimed to validate the General Attitudes towards Artificial Intelligence Scale (GAAIS; Schepman & Rodway, 2020, 2023) in Italian, considering people's level of epistemic trust, across two Italian samples. The first aim of the study was to adapt the GAAIS scale to

Table 7
Factor loadings Study 2.

						95 % Confidence Interval			
Factor	**Indicator**	**Estimate**	**Std. Error**	**z-value**	**p**	**Lower**	**Upper**	**Mean**	**Std. Deviation**
GAAIS_POSITIVE									
	GAAIS_1	0.496	0.102	4.861	<0.001	0.296	0.696	2.802	1.137
	GAAIS_2	0.606	0.082	7.396	<0.001	0.445	0.767	3.570	0.973
	GAAIS_4	0.725	0.083	8.764	<0.001	0.563	0.888	2.934	1.023
	GAAIS_5	0.492	0.078	6.305	<0.001	0.339	0.645	4.058	0.897
	GAAIS_7	0.825	0.080	10.314	<0.001	0.668	0.982	3.587	1.038
	GAAIS_11	0.715	0.069	10.286	<0.001	0.579	0.851	3.587	0.901
	GAAIS_12	0.664	0.066	10.132	<0.001	0.536	0.793	3.645	0.845
	GAAIS_13	0.410	0.093	4.392	<0.001	0.227	0.592	3.124	1.029
	GAAIS_14	0.480	0.059	8.108	<0.001	0.364	0.596	4.066	0.716
	GAAIS_16	0.311	0.088	3.531	<0.001	0.138	0.484	3.488	0.958
	GAAIS_17	0.657	0.079	8.342	<0.001	0.502	0.811	3.248	0.960
	GAAIS_18	0.821	0.087	9.440	<0.001	0.650	0.991	3.281	1.097
GAAIS_NEGATIVE									
	GAAIS_3	0.502	0.079	6.356	<0.001	0.347	0.657	2.760	0.885
	GAAIS_6	0.185	0.075	2.460	0.014	0.038	0.333	2.686	0.786
	GAAIS_8	0.849	0.084	10.156	<0.001	0.685	1.013	3.215	1.050
	GAAIS_9	0.478	0.094	5.071	<0.001	0.293	0.663	3.430	1.023
	GAAIS_10	0.688	0.085	8.089	<0.001	0.521	0.854	2.777	1.004
	GAAIS_15	0.858	0.089	9.634	<0.001	0.684	1.033	2.983	1.103
	GAAIS_19	0.581	0.090	6.478	<0.001	0.405	0.757	3.248	1.002
	GAAIS_20	0.409	0.092	4.472	<0.001	0.230	0.589	3.273	0.983

Table 8
Study 2 goodness-of-fit indices generated by multigroup Confirmatory Factor Analysis (CFA) across gender with and without modification indices.

	Recommended value	Value obtained without MI	Value obtained with MI
X^2/df	≤3.00	1.513	1.448
CFI	≥0.90	0.823	0.847
TLI	≥0.90	0.800	0.825
SRMR	≤0.08	0.101	0.099
RMSEA	≤0.08	0.092 ([CI] = 0.075–0.108)	0.086 ([CI] = 0.069–0.103)

Italian and investigate its validity and reliability in an adult Italian sampling. In Study 1, CFA findings demonstrated that the factor structure was confirmed in the present study. Previous findings have indicated that the GAAIS had satisfactory evidence regarding the internal consistency reliability: Cronbach's α was 0.88 for the positive GAAIS and 0.83 for the negative GAAIS (Schepman & Rodway, 2020) and replicated as 0.88 and 0.82 for the positive and negative GAAIS respectively (Schepman & Rodway, 2023). It was replicated also in the Turkish sample, where Cronbach's α was 0.82 for the GAAIS-P and 0.84 for the GAAIS-N (Kaya et al., 2024). The present study revealed similar results: Cronbach's α demonstrated high internal consistency in our study with the Italian sample. The literature suggests that results equal to 0.70 and above is sign of adequate internal consistency (Nunnally & Bernstein, 1994; Black & Babin, 2019). The data from the CFA and internal consistency and reliability assessments demonstrated the validity of the Italian GAAIS. The results of the factor loadings analysis provided important insights into the GAAIS factors. The strength and significance of the loadings suggest that the examined indicators effectively represent the underlying constructs. For the GAAIS-P, the indicators exhibited loadings ranging from 0.311 to 0.825. Notably, items 7 (0.825) and 18 (0.821) showed the highest loadings, indicating a strong correlation with the positive construct. The statistical significance of all indicators ($p < 0.001$) confirms that these results are robust and reliable. Moreover, the 95 % confidence intervals for each indicator further support the validity of the estimates, highlighting the stability of the loadings within the analyzed sample. Similarly, for the negative factor, the loadings of the indicators ranged from 0.185 to 0.858. In particular, items 8 (0.849) and 15 (0.858) were the most representative, suggesting that these items can effectively capture individuals' negative experiences. It is important to note that while item 6 displayed a loading of 0.185 ($p = 0.014$), indicating statistical significance, the value is relatively low compared to other indicators. This may suggest that the indicator in question is less representative of the construct compared to others and warrants further investigation.

6.2. The dual nature of AI attitudes

Our correlation analysis revealed a significant positive relationship between the GAAIS-P and GAAIS-N factors, providing insights into the coexistence of positive and negative attitudes towards AI. This positive correlation suggested that individuals who hold favorable attitudes toward AI (higher scores on the positive GAAIS) also tend to be more accepting of its drawbacks (higher scores on the reverse-scored negative GAAIS). Individuals who appreciate the benefits of AI are also more likely to display tolerance towards its limitations. However, the fact that the correlation was of moderate strength suggests a level of independence between the two factors, indicating that some individuals can hold ambivalent attitudes towards AI.

This finding aligns with the interpretation that enthusiasm for AI positive aspects might promote a more forgiving attitude towards its

Table 9
Correlations analysis results.

		Age	Gender	Education	Job	AI Knowledge	Computer use	ETMCQ_ET	ETMCQ_EM	ETMCQ_EC
GAAIS-P	Pearson Correlation	0.018	−0.280**	−0.041	−0.055	0.404**	0.175	−0.112	−0.033	−0.127
	Sig. (2-tailed)	0.842	0.002	0.654	0.548	<0.001	0.053	0.220	0.721	0.162
	N	122	122	122	122	122	122	122	122	122
GAAIS-N	Pearson Correlation	0.005	−0.068	0.126	−0.084	0.083	0.000	−0.099	−0.303**	−0.172
	Sig. (2-tailed)	0.960	0.459	0.167	0.355	0.366	0.997	0.280	<0.001	0.059
	N	122	122	122	122	122	122	122	122	122

Table 10
Hierarchical multiple linear regression analysis on the predictive role of various variables on positive attitudes toward artificial intelligence.

	Model I					Model II					Model III				
Variable	*B*	*SE*	*β*	*t*	*p*	*B*	*SE*	*β*	*t*	*p*	*B*	*SE*	*β*	*t*	*p*
Constant	3.592	0.197		18.247	<0.001	3.114	0.686		4.540	<0.001	3.796	0.755		5.025	<0.001
Gender	−0.346	0.109	−0.280	−3.183	0.002	−0.207	0.116	−0.168	−1.781	0.077	−0.213	0.116	−0.173	−1.848	0.067
Age	0.001	0.005	0.016	0.180	0.857	−0.001	0.005	−0.016	−0.184	0.854	−0.004	0.005	−0.068	−0.774	0.440
Education						−0.061	0.081	−0.069	−0.760	0.449	−0.036	0.082	−0.040	−0.436	0.664
AI Knowledge						0.372	0.094	0.389	3.965	<0.001	0.400	0.094	0.418	4.250	<0.001
Computer use						−0.074	0.124	−0.060	−0.598	0.551	−0.080	0.126	−0.065	−0.635	0.527
Employment status						0.032	0.104	0.029	0.310	0.757	0.083	0.107	0.075	0.782	0.436
ETMCQ_ET											−0.101	0.066	−0.148	−1.539	0.127
ETMCQ_EM											−0.068	0.069	−0.087	−0.985	0.327
ETMCQ_EC											−0.028	0.054	−0.051	−0.520	0.604
R^2	0.079					0.195					0.228				
Adjusted R^2	0.063					0.153					0.166				
F for Change in R^2	5.088					4.134					1.619				

Table 11
Hierarchical multiple linear regression analysis on the predictive role of various variables on negative attitudes toward artificial intelligence.

	Model I					Model II					Model III				
Variable	*B*	*SE*	*β*	*t*	*p*	*B*	*SE*	*β*	*t*	*p*	*B*	*SE*	*β*	*t*	*p*
Constant	3.093	0.207		14.953	<0.001	2.807	0.762		3.684	<0.001	4.056	0.804		5.047	<0.001
Gender	−0.084	0.114	−0.068	−0.740	0.461	−0.089	0.129	−0.071	−0.688	0.493	−0.113	0.123	−0.090	−0.917	0.361
Age	0.000	0.005	0.004	0.044	0.965	0.000	0.005	0.004	0.047	0.962	−0.003	0.005	−0.052	−0.564	0.574
Education						0.099	0.090	0.109	1.100	0.274	0.119	0.087	0.131	1.361	0.176
AI Knowledge						0.062	0.104	0.064	0.591	0.556	0.106	0.100	0.109	1.057	0.293
Computer use						−0.080	0.138	−0.064	−0.581	0.562	−0.086	0.134	−0.068	−0.639	0.524
employment status						−0.046	0.116	−0.041	−0.397	0.692	0.057	0.113	0.051	0.507	0.613
ETMCQ_ET											−0.080	0.070	−0.116	−1.145	0.255
ETMCQ_EM											−0.230	0.073	−0.293	−3.149	0.002
ETMCQ_EC											−0.059	0.058	−0.105	−1.022	0.309
R^2	0.005					0.027					0.145				
Adjusted R^2	−0.012					−0.023					0.077				
F for Change in R^2	0.275					0.671					5.151				

potential downsides, reinforcing the notion that overall acceptance of AI may be closely tied to balanced perceptions of both its strengths and its limitations. It is important to recognize the practical and policy implications of the dual nature of AI attitudes, particularly within educational contexts. This ambivalence underscores the need to foster a balanced and critical discourse around AI, aiming to promote informed and realistic forms of acceptance (Walter, 2024). Such a discourse should encourage the systematic examination of both the promises and the limitations of AI, ensuring that neither is overlooked. By doing so, educators and institutions can help prevent overconfidence or uncritical enthusiasm, supporting the development of reflective, ethically aware, and resilient engagement with emerging technologies.

6.3. The social profile of AI attitudes

Gender emerged as a significant predictor of positive attitudes toward AI, suggesting that females tend to be more skeptical of AI compared to males. These findings are consistent with studies that highlight males generally more positive attitudes toward AI technologies than those of females (Schepman & Rodway, 2023; Sindermann et al., 2021, 2022; Zhang & Dafoe, 2019). Furthermore, research often emphasizes that males show greater interest in technological advancements and, concerningly, are also more susceptible to developing addictive behaviors associated with technology (Su et al., 2019). Another significant predictor of positive attitudes toward AI was the level of knowledge about AI. This is in line with previous works where people with higher level of AI knowledge have more positive attitudes toward AI (Belanche et al., 2019; Mantello, Ghotbi, Ho, & Mizutani, 2024; Kaya et al., 2024). In other words, a deeper understanding of AI seems to be related to a more optimistic attitude towards AI. This finding is particularly relevant to issues of AI acceptance, and highlights the potential benefits of AI education in shaping positive perceptions among people. On the other hand, those with positive attitudes might be more driven to learn about AI. Whilst the promotion of AI literacy remains of critical importance, it is important that educational programs also incorporate critical content regarding risks, ethical concerns, and governance issues to cultivate informed attitudes (Walter, 2024).

Regarding other demographic characteristics, our study showed no significant values as a predictor of AI, in contrast with previous literature. For instance, regarding age there are conflicting findings, where Park and colleagues (2022) found that older people are more accepting of new technologies than younger people, while another part of the literature states that younger people have more positive attitudes towards AI (European Commission & Directorate-General for Communications Networks, Content & Technology, 2017). Also, Schepman and Rodway (2023) found that younger people had more positive attitudes toward both positive and negative aspects of AI. It is necessary to provide a more nuanced understanding of this issue, especially in the Italian context, where the debate about AI is particularly lively and multifaceted. This complexity arises from varying public opinions, media coverage, and different cultural perspectives, all of which contribute to shaping attitudes towards AI.

Beyond age and broader cultural influences, educational level also did not significantly predict attitudes towards AI, in line with findings from other GAAIS validation studies (Kaya et al., 2024). This result might reflect a limited variability in education levels within the sample, or suggest that general education does not directly translate into AI-specific literacy or ethical sensitivity. Interestingly, Masayuki (2016) found that companies with more highly educated employees display more positive attitudes towards AI compared to those with less educated workforce. However, this finding may reflect context-specific factors, such as the cultural and organizational norms prevalent in Japanese companies. Our lack of a significant association could thus be attributed to these contextual differences, underscoring the importance of cross-cultural comparisons. Moreover, general education does not equate to specific AI education, a distinction relevant for these findings. In line with our results, knowledge about AI, rather than general education, significantly predicted attitudes toward AI, suggesting that targeted educational interventions are needed to shape informed attitudes toward these emerging technologies.

Computer use did not significantly predict attitudes toward AI in our study, in contrast with previous research that reported a positive association between computer use and positive AI perceptions (Kaya et al., 2024). Similarly, other studies have shown that individuals with greater technological expertise tend to view AI more positively than those with limited experience (Vu & Lim, 2022; Zhang & Dafoe, 2019). One possible explanation is that technological familiarity fosters a sense of control and efficacy, which can reduce fear and increase trust (Pintos dos Santos et al., 2019). An alternative interpretation draws on cognitive biases. Individuals with high enthusiasm for technology might exhibit confirmation bias or overconfidence, leading them to overestimate the benefits of AI, underestimate risks, or believe they can fully control AI systems (Said et al., 2023). This underscores the importance of critical and reflective educational interventions that balance technological optimism with ethical and societal considerations.

Cultural context also emerged as a key source of difference. The differences between the Turkish (Kaya et al., 2024) and Italian samples in AI knowledge and usage may help explain why some demographic predictors failed to replicate. These discrepancies highlight the need to extend validation studies of tools like the GAAIS to diverse cultural contexts to better understand how attitudes are shaped not only by individual variables, but also by cultural context. Attitudes toward AI are not only psychological dispositions but socio-cultural constructs, rooted in everyday interactions with algorithmic systems (Airoldi, 2021). The Italian validation of the GAAIS reflects this by attempting to capture culturally embedded expectations surrounding AI. For a broader comprehension of these attitudes, it is important also to consider constructs such as perceived human autonomy and emotional expressiveness, which vary across cultures and influence trust and acceptance (Ho et al., 2024; Ho & Luu, 2025). Recent integrative frameworks, such as the Three-Pronged Approach (Ho et al., 2023) combine the Technology Acceptance Model (TAM; Davis, 1989) with Moral Foundations Theory (Haidt, 2007), offering a multidimensional perspective on how morality and judgments jointly shape AI attitudes. These frameworks could be useful for explaining cross-cultural differences in the predictive power of demographic variables (e.g., Italy vs. Turkey), by accounting for culturally specific emotional and moral schemas. As emotionally responsive and autonomous AI becomes increasingly integrated into daily life, policies and educational initiatives must adopt integrative approaches that consider cognitive, emotional, and cultural dimensions.

Practically, these findings highlight the need for inclusive and context-sensitive strategies. The observed gender gap points to targeted educational efforts, while the impact of AI-specific knowledge, unlike general education or computer use, underscores the limits of generic digital literacy programs. This calls for curricula tailored to the ethical, psychological, and functional dimensions of AI. Moreover, the weak predictive power of traditional sociodemographic variables reinforces the need for socially responsive interventions. Policymakers should promote diverse and transparent AI governance, ensuring that underrepresented groups are meaningfully included in shaping AI's societal role.

6.4. Trust dynamics in AI attitudes

Our findings indicate a significant relationship between trust and attitudes toward AI, particularly highlighting the role of Epistemic Mistrust (EM)—the tendency to perceive sources of information, including individuals, as unreliable or malevolent (Campbell et al., 2021). EM was found to be negatively correlated with the Negative subscale of the GAAIS. This suggests that individuals who are more distrustful of human sources of knowledge are also less forgiving of AI drawbacks. This relationship between human trust and AI trust aligns

with a broader intuition. Those who harbor deep skepticism toward humans may extend their distrust to technology, focusing more on the potential risks and shortcomings of AI. Understanding this dynamic is vital for fostering AI acceptance. While general trust is positively associated with favorable attitudes toward AI, as evidenced by its correlation with the Positive subscale of the GAAIS, epistemic mistrust, along with corporate distrust (Schepman & Rodway, 2023), appears to drive more critical views. These attitudes are particularly evident in concerns about AI risks and are influenced by broader trust dynamics. Individuals' perceptions of institutions, as well as the motives behind AI development, play a significant role in shaping their acceptance of the technology. Addressing public trust in institutions and ensuring transparent AI development processes may be critical to building legitimate public engagement with AI technologies. Moreover, addressing these underlying trust factors may be essential for promoting more balanced perspectives on AI. Additionally, the lack of significant effects for other variables like gender, age, education, occupation, computer use, AI knowledge, and other trust subscales suggests that demographic factors and AI knowledge did not play a meaningful role in shaping individuals' negative attitudes toward AI in this model.

From a psychological and policy perspective, these findings highlight the need for interventions that go beyond factual AI education to address deeper trust dynamics. Programs should promote epistemic awareness, helping individuals critically evaluate information, recognize manipulation, and tolerate uncertainty, thus reducing both fear and overconfidence. Given the role of epistemic mistrust, it is important to foster reflective trust in institutions and communicators. This calls for transparent, inclusive, and participatory communication strategies, particularly in education and public policy, to support informed and balanced engagement with AI. For example, in the healthcare sector, introducing AI-driven tools requires not only technical reliability but also clear communication about how decisions are made, what limitations exist, and who remains accountable. Addressing patients' epistemic mistrust through accessible explanations and shared decision-making can enhance trust and acceptance, especially in emotionally and ethically sensitive contexts.

7. Conclusions

We validated the GAAIS in Italian, demonstrating its comparability to the English and Turkish versions (Schepman & Rodway, 2020, 2023; Kaya et al., 2024). Our study replicates the factor structure observed in these earlier versions, supporting the cross-cultural robustness of the scale. Gender emerged as a significant predictor, with females exhibiting less favorable attitudes toward AI than males, consistent with previous research. AI knowledge also positively influenced attitudes, aligning with studies linking greater understanding to more positive perceptions. Interesting, other demographic factors, including age, education level, and computer use, were not significant predictors, diverging from some existing literature and suggesting potential cultural or contextual moderators.

A key contribution of this study is the association between epistemic mistrust - defined as skepticism toward information sources - and negative attitudes toward AI drawbacks. This suggests that distrust in human sources of knowledge may extend to distrust in artificial ones, particularly when evaluating the risks and limitations of AI systems. These concerns are echoed in recent studies on emotional AI in healthcare, education and domestic environments, which show that moral risk awareness and perceived intentions behind AI deployment play a central role in public acceptance.

The findings emphasize the necessity of addressing more extensive trust dynamics, including institutional trust and perceived developer intentions, as opposed to concentrating exclusively on AI knowledge. From a psychological perspective, the promotion of critical thinking, metacognitive awareness, and epistemic vigilance through education and communication strategies may foster more adaptive, cautious, and balanced attitudes towards AI technologies.

8. Future work and limitations

The present study acknowledges several limitations that also open valuable avenues for future research. Firstly, while this research offers a culturally grounded contribution through the Italian validation of the GAAIS, it did not include direct measures of cultural orientation. To enhance comprehension of the cultural modulation of AI attitudes, it is recommended that future studies adopt cross-cultural comparative designs and incorporate cultural variables such as individualism–collectivism. Secondly, although the present study focused on dimensions of epistemic and epistemic trust, there are other psychologically relevant constructs that require further exploration. These include emotional responses to AI, moral intuitions, perceived agency, and anthropomorphization processes, all of which have the potential to significantly influence engagement with AI systems. Furthermore, the study showed that epistemic mistrust exerts a pivotal influence in the formation of adverse perceptions concerning AI risks. Future research should build on this by exploring how epistemic vigilance, critical thinking, and trust repair mechanisms interact with technological trust in different domains (e.g., healthcare, education, workplace). Finally, while our statistical approach was robust and aligned with psychometric standards, future research could benefit from complementary methods such as Bayesian Network modelling and Network Psychometrics (e.g., Borsboom et al., 2021; Mantello et al., 2023). These approaches may help capture the dynamic interplay between trust, knowledge, and emotional responses, offering richer insights into the evolving landscape of AI attitudes.

CRediT authorship contribution statement

F. Sacco: Writing – original draft, Methodology, Formal analysis, Conceptualization. **F. Manzi:** Writing – review & editing, Methodology, Formal analysis, Conceptualization. **C. Di Dio:** Writing – review & editing. **A. Schepman:** Writing – review & editing, Methodology. **P. Rodway:** Writing – review & editing, Methodology. **D. Massaro:** Writing – review & editing. **A. Marchetti:** Writing – review & editing, Supervision.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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Data availability

Data will be made available on request.

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