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Between Trust and Anxiety: Citizen Attitudes to AI in Emilia-Romagna.

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Abstract

Artificial Intelligence (AI) has rapidly moved from expert arenas into everyday life, acquiring strong symbolic and cultural relevance within contemporary social conversations around science. Despite increasing familiarity with AI technologies, public attitudes remain ambivalent and polarized, challenging deficit-based assumptions that link scientific knowledge to positive technological orientations.

Adopting an interpretative Public Understanding of Science framework, this study examines how scientific literacy, trust in science, and exposure to AI-related content interact in shaping public attitudes toward AI. The analysis draws on data from the 2025 Observa Science in Society Monitor, a representative survey conducted in the Emilia-Romagna region (n = 502). Latent Class Analysis identifies four distinct attitudinal profiles—techno-ambivalent, techno-optimist, techno-skeptic, and techno-phobic—which are subsequently analyzed using multinomial logistic regression.

Results show that trust in science is the most robust predictor of techno-optimistic attitudes, outweighing the effects of scientific literacy and media exposure. Moreover, exposure to AI-related content has conditional effects: among individuals with low trust in science, higher exposure increases the likelihood of techno-phobic orientations, while this association disappears among high-trust respondents. Overall, the findings highlight the central role of trust in science in shaping differentiated public responses to emerging technologies beyond deficit-based explanations.

Keywords: Artificial intelligence, public perception, technology and society, science in society, emotions.

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1. Introduction

Artificial Intelligence (AI) is now a constant presence in the daily lives of millions of people. From social networks to online shopping, from voice assistants to systems that support both public and private decision-making processes, AI-based technologies are changing the way we work, communicate, and stay informed.

The rapid growth of Big Data (Floridi, 2012) contributed to the acceleration of the development of AI (Strauß, 2018), substantially re-defining power dynamics in knowledge discovery (Balazka & Rodighiero, 2020). Despite the unprecedented opportunities and the many benefits of AI, the attention of the scientific community has quickly shifted to examining the impact of persistent biases in the training data (Paullada et al., 2021) and various other design choices (Hooker, 2021) on its effective fairness and trustworthiness. Studies have shown, for example, how gender and racial biases affect the implementation of face recognition technologies (Boulamwini & Gebru, 2018) or how minorities are misrepresented and stereotyped in Large Language Models (Liu, 2024; Shujaa et al., 2025).

Beyond its technical applications, AI has rapidly acquired symbolic and cultural significance, becoming a prominent topic within what Bucchi and Trench (2021) describe as the "social conversation(s) around science". Since the public release of ChatGPT in November 2022, AI has moved decisively from expert and policy arenas into popular culture, media narratives, and everyday discourse, circulating through news outlets, social media platforms, artistic productions, and informal social settings. As observed with earlier technoscientific innovations, this expansion of visibility has been accompanied by polarized representations, oscillating between alarmist framings and narratives of uncritical technological optimism (Bucchi, 2010; Acerbi, 2025), creating a rather complex situation in the public perception of this technology.

Indeed, empirical research on public attitudes toward AI suggests a complex and sometimes contradictory picture. While levels of familiarity and reported use of AI technologies have increased significantly across Western countries (CDEI, 2024; Pew Research Center, 2025; Eurostat, 2025), such exposure has not led to a proportional decline in public concern. On the contrary, citizens continue to express ambivalence and anxiety regarding the ethical, social, economic, and political implications of AI systems (Sindermann et al., 2021; Ipsos, 2024; European Commission, 2025). 23% of Americans believe that the impact of AI will be "very negative" or "mostly negative" (Northeastern University & Gallup, 2018), while Eurobarometer (European Commission, 2019) data showed that 43% of European citizens (42% in Italy) said they were concerned about liability issues that could arise with the use of AI.

Gender differences remain persistent across national contexts, with women consistently reporting lower levels of perceived safety and anticipated benefits compared to men, including among AI professionals (European Commission, 2017; Pew Research Center, 2025). Similarly, previous research frequently stresses the existence of a generational gap (Czaja & Sharit, 1998; Kubovics, 2025), with older respondents generally opposing new technologies more strongly. The effect of education is more nuanced, with higher educational levels being positively associated with a stronger perceived usefulness of AI, but often unrelated to its perceived fairness or risk (Araujo et al., 2020).

Taken together, these findings challenge simplified assumptions about the relationship between knowledge and attitudes toward science and technology. While early approaches within the Public Understanding of Science tradition were grounded in a "deficit model"—which posited that public skepticism derives primarily from a lack of scientific knowledge—subsequent research has produced mixed results. According to the deficit model, there is a linear relationship between public understanding of science and technology and favorable attitudes toward it.

In other words, the mistrust, skepticism or public hostility of non-experts is simply attributed to their lack of information and understanding of the world of research (Bucchi & Neresini, 2002). This pedagogical-paternalistic conception posits that an adequate public communication will lead to the establishment of a positive and supportive attitude toward the techno-scientific enterprise among the wider population (Irwin & Wynne, 1996).

Some studies suggest that increased knowledge correlates with more positive attitudes (Turney, 1998; Lewenstein, 1992), whereas others indicate that greater familiarity may foster critical awareness and caution (Collins & Pinch, 1998; Pew Research Center, 2025), such as has recently been observed in a study on AI deepfake technology (Denia & Durant, 2026). As Bucchi (2010) argues, such inconsistencies reveal the limitations of linear and cognitive models of public understanding, calling instead for interpretative and contextual approaches that account for trust, cultural meanings, social identities, and media environments.

From this critical perspective, public attitudes toward AI cannot be reduced to informational gaps or levels of scientific literacy alone. Rather, they are shaped by broader relational and contextual factors, including trust in science and scientific institutions, perceptions of expertise, media framings, and prior experiences with science and technology. Nevertheless, it is important to note that the scientific community has often questioned, and sometimes even worried about (O'Brien et al., 2021), the degree of trust that citizens place in science. One wonders whether there really is a 'crisis of trust in science' (Millstone & van Zwanenberg, 2000) or, as some authoritative observers argue, a real 'war on science' (Achenbach, 2015; Krauss, 2025) due to the emergence of a widespread pseudoscientific culture (Tipaldo, 2019).

In line with the interpretative turn in Public Understanding of Science (PUS) studies (Wynne, 1995; Michael, 2002; Bucchi, 2010), this research adopts a multidimensional approach to the analysis of public perceptions of AI, emphasizing the interplay between knowledge, trust, and communicative contexts.

Empirically, the paper investigates citizens' attitudes toward AI in the Italian region of Emilia-Romagna, using data from the 2025 Science in Society Monitor survey. In 2025, Bologna (the chief town of Emilia-Romagna), surpassed for the first time Milan–Italy's leading economic center and the city with the highest GDP per inhabitant–in the ranking of Italian smart cities (City Vision, 2025). For more than a decade, the Emilia-Romagna Region has been involving institutions, the research and training sector, and businesses in Data Valley, a cutting-edge project aimed at making the region a European incubator capable of attracting investment, resources, and skills. This area of Italy is home to CINECA, a supercomputing center for scientific research in Italy, and in 2022, LEONARDO, one of the eight pre-exascale supercomputers that make up the European high-performance computing network EuroHPC, was installed at the Bologna Technopole. This achievement reflects Emilia-Romagna's broader positioning as a dynamic and innovation-oriented region, increasingly investing in digital transformation and smart solutions. Precisely because it represents such a dynamic and digitally advancing regional context, Emilia-Romagna provides a particularly suitable setting to examine how scientific literacy, trust in science, media exposure, and socio-demographic variables interact in shaping differentiated attitudinal profiles toward AI.

In light of these considerations, the study addresses the following research question: how do scientific literacy, trust in science, and exposure to scientific content interact in shaping the likelihood of belonging to an optimistic or pessimistic attitudinal profile toward Artificial Intelligence?

By empirically testing key assumptions of the critical/interpretative public understanding of science framework, this study contributes to ongoing debates on how citizens make sense of emerging technologies beyond deficit-based explanations. While the findings should not be uncritically generalized to other contexts, they offer analytically grounded insights into the sociocultural dynamics underlying public perceptions of AI and the conditions under which trust in science becomes a pivotal factor in shaping attitudes toward technological change.

2. Data and methods

The data come from a representative survey conducted as part of the project "Artificial Intelligence in Emilia-Romagna." Data collection took place between July 15 and July 29, 2025, using a mixed-mode design combining online interviews (CAWI) and telephone interviews (CATI). A total of 502 interviews were completed, including 252 CAWI and 250 CATI interviews. The sample of the adult population residing in Emilia-Romagna was defined using gender and age group as stratification variables. To correct for potential sampling biases related to educational attainment, post-stratification weights – stratified by gender – were calculated using official statistics from the Emilia-Romagna Region. All analyses reported in this study are based on weighted data. The analysis was conducted using Stata 17. Selected figures were prepared in Python 3.11.3.

The dependent variable is a categorical construct derived from a battery of items measuring attitudes toward AI. The respondents were asked to indicate, on a scale from 1 to 10, the extent to which they feel trust, expectation, suspicion, anxiety, and worry when thinking about AI. The battery was processed using Latent Class Analysis (Weller et al., 2020). Because respondents may use response scales differently, potentially leading to response style bias (He et al., 2021), the scores were ipsatized prior to the analysis. Ipsatization subtracts, for each respondent, his or her overall mean from each item composing the battery. Ipsatized scores therefore represent deviations from a respondent's average, allowing the analysis to uncover relative prioritization patterns in the data more clearly (Schwartz, 2006). A detailed overview of the characteristics of each of the four identified classes is presented in the following section.

Scientific literacy was measured using a battery of five true/false statements designed to capture respondents' basic factual knowledge of science and technology. The statements covered core scientific concepts and included: electrons are smaller than atoms (true), antibiotics kill both viruses and bacteria (false), the sun is a planet (false), nitrogen is the most abundant element in the air (true), and the bit is the unit of measurement of information (true). Each correct response was coded as 1 and incorrect responses as 0, and the items were summed to create an index ranging from 0 to 5. For ease of interpretation and comparability in multivariate analyses, the index was linearly normalized to range from 0 to 10. The resulting scientific literacy measure has a mean of 6.3 and a standard deviation of 2.7.

Trust in science was measured using an index constructed from a battery of items capturing trust in science in general, research institutes, and scientists. Respondents were asked to indicate how trustworthy they considered each of these actors, with response options ranging from not at all (1) to very (4) trustworthy. An additional item measuring trust in experts who participate in public debates (e.g., on television or social media) exhibited substantially lower factor loadings and high uniqueness. Moreover, internal consistency analyses indicated that this item significantly reduced the reliability of the scale. For these reasons, the item was excluded from subsequent analyses. Exploratory factor analysis (EFA) identified a single factor with an eigenvalue greater than 1. All retained items loaded strongly on the latent factor, with factor loadings ranging from .75 to .84, and exhibited low uniqueness values, consistently below the .50 threshold. The resulting scale demonstrated very good internal consistency, with a Cronbach's alpha of 0.85 and an average interitem correlation of 0.66. The trust in science index was computed as the average of the three retained items and was subsequently linearly normalized to range from 0 to 10. The final normalized variable has a mean of 7.7 and a standard deviation of 1.9.

Finally, exposure to AI-related content was measured using a mentioned/not-mentioned battery asking respondents to indicate the contexts in which they had heard about Artificial Intelligence during the previous year. Respondents could mention multiple sources from a predefined list, including television and/or radio, newspapers or online press, social media, books, films and television series, advertising, relatives or friends, and scientists. Each mentioned source was coded as 1 and unmentioned sources as 0, and the items were summed to construct an additive index capturing the breadth of AI-related exposure across information environments. The resulting index ranges from 0 (no sources mentioned) to 8 (all sources mentioned). For ease of interpretation in multivariate analyses, the index was linearly normalized to range from 0 to 10. The normalized exposure measure has a mean of 3.8 and a standard deviation of 2.5.

We examine how exposure to AI-related content, trust in science, and scientific literacy are associated with latent profiles of attitudes toward Artificial Intelligence using multinomial logistic regression. The dependent variable captures four distinct attitude profiles, with a mixed-evaluation profile serving as the reference category, alongside an optimistic profile characterized by high positive and low negative feelings toward AI, a skeptical profile in which negative feelings prevail over positive ones, and a phobic profile marked by high negative and low positive feelings. Based on prior research, we advance two main hypotheses. H1 posits that higher levels of scientific literacy are positively associated with membership in more favorable AI attitude profiles – particularly the optimistic class – and negatively associated with membership in skeptical and phobic profiles. H2 posits that trust in science moderates the association between exposure to AI-related content and AI attitude profiles. Specifically, among individuals with low trust in science, greater exposure is expected to increase the likelihood of belonging to skeptical profiles, especially the phobic class. In contrast, among individuals with high trust in science, greater exposure is expected to reduce the likelihood of skeptical and phobic profiles and increase the likelihood of membership in the optimistic profile. All models control for gender, age, and educational attainment.

3. Identifying latent profiles of attitudes toward AI

To identify distinct profiles of attitudes toward AI, a Latent Class Analysis was conducted using ipsatized versions of five attitudinal indicators (trust, expectation, suspicion, anxiety, and worry). The analysis yielded four latent classes, representing qualitatively different profiles of public sentiment toward this emerging technology.

Table 1 – Goodness of fit statistics of LCA models by number of latent classes

Number of classes	1	2	3	4	5
AIC	10424.1	9688.8	9298.9	9139.9	9087.0
ΔAIC		-735.3	-389.9	-159.0	-52.9
BIC	10466.3	9756.3	9391.7	9258.0	9230.4
ΔBIC		-710.0	-364.6	-133.7	-27.6

As shown in Table 1, both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) decrease as the number of latent classes increases, indicating improved model fit. The improvement is particularly strong when moving from a one-class to a two-class solution and remains substantial when increasing to three and four classes. However, the improvement markedly slows down with a five-class solution, suggesting diminishing returns from additional complexity. Qualitative considerations further support the four-class solution. Compared to the three-class model, the four-class solution provides a theoretically more meaningful distinction, as it differentiates between two distinct forms of negative attitudes toward AI. The four resulting groups also maintain sufficient sample size for subsequent analyses, and the differences between classes remain statistically significant across all items. In contrast, the five-class solution produces smaller groups with overlapping profiles across several dimensions, reducing interpretability and practical usefulness.

Fig. 1 – Average level (95% confidence interval) of trust, expectation, suspicion, anxiety, and worry evoked by AI clustered by latent profile of the respondent, Emilia-Romagna 2025 (n = 502).

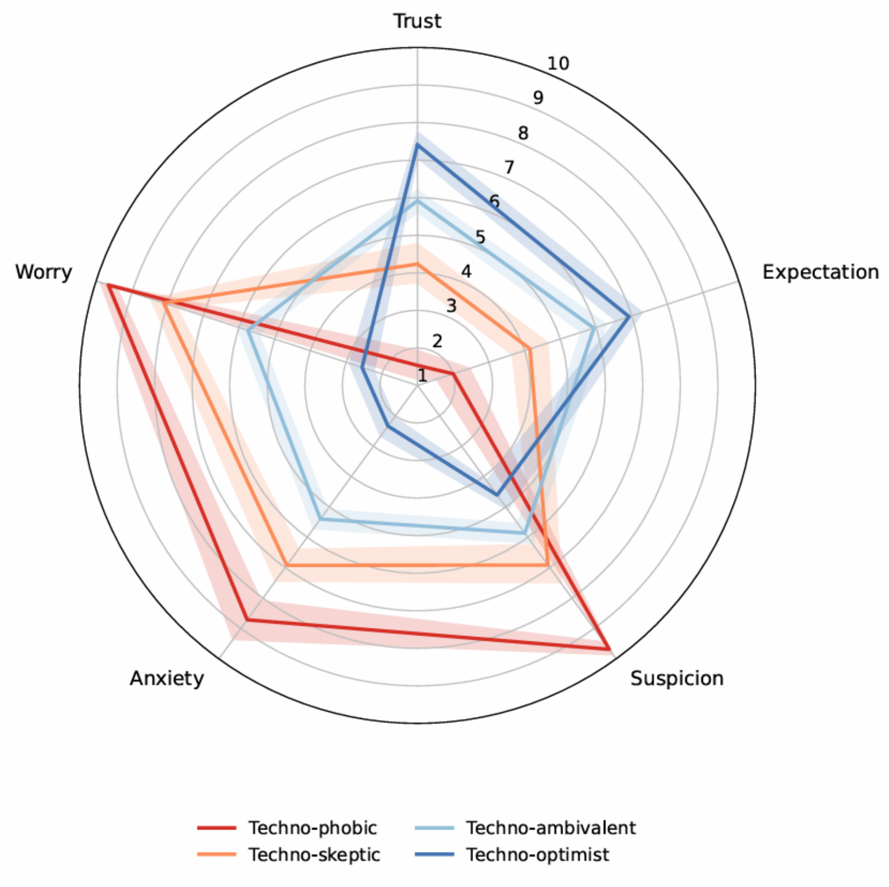


Figure 1 portrays the average levels of trust, expectation, suspicion, anxiety, and worry evoked by AI for each of the identified latent classes. These groupings can be characterized as follows:

Techno-ambivalent. This is the largest of the four categories: 48.3% of the sample is classified as techno-ambivalent. The group is characterized by a balanced mix of positive and negative attitudes, with scores clustered around the midpoint of the scale. Trust and expectation both average 5.9, while suspicion (5.9), worry (5.8) and anxiety (5.4) are similarly moderate and closely aligned. Overall, the profile suggests a generally cautious but not overly negative or positive stance toward AI.

Techno-skeptic. The second largest category is that of techno-skeptics, comprising 25.7% of the sample. This group is characterized by modestly positive attitudes, with both trust and expectation averaging 4.2, alongside a prevalence of negative feelings toward AI. Suspicion and anxiety are moderately high (6.9 each), while worry is particularly elevated, with an average score of 8.1. Overall, this profile reflects a cautious stance toward AI, combining mild trust with strong concerns.

Techno-optimist. This category represents 17.9% of the sample. Members of this group show strong positive attitudes toward AI, with high levels of trust (7.4) and expectation (6.9). Negative emotions are instead very low: suspicion averages 4.6, anxiety 2.3, and worry 2.6. Overall, techno-optimists are characterized by confidence in AI and low concern about its risks.

Techno-phobic. The smallest category, 8.2% of the sample, consists of techno-phobics. This group displays very low trust and expectation (1.5 and 2.0, respectively) alongside extremely high negative reactions. Suspicion and worry both average 9.7, while anxiety reaches 8.7. Overall, techno-phobics are strongly averse to AI, exhibiting intense fear and distrust.

4. Results

This section examines the determinants of latent class membership related to attitudes toward technology, focusing on both individual characteristics and the interplay between exposure to AI-related content and trust in science. By comparing techno-optimist, techno-skeptic, and techno-phobic respondents to the reference group of techno-ambivalent individuals, the analysis highlights how cognitive, experiential, and sociodemographic factors shape heterogeneous attitudinal responses to emerging technologies. In particular, introducing an interaction between AI exposure and trust in science allows us to explore whether the effects of engagement with AI-related information differ depending on the level of confidence in science.

Table 2 presents multinomial logistic regression models predicting membership in three latent classes (i.e., techno-optimist, techno-skeptic, and techno-phobic) relative to the reference category of techno-ambivalent respondents. Model 1 (M1) includes only main effects, while Model 2 (M2) introduces the interaction between exposure to AI and trust in science. Both models use sampling weights to correct for educational imbalance among respondents.

Tab.2 – Multinomial Logistic Regression predicting membership in latent classes of attitudes toward AI (Emilia-Romagna 2025, n = 500).

Latent Class (ref. Techno-ambivalent)	Labels	M1 Relative Risk Ratio	M1 S.E.	M2 Relative Risk Ratio	M2 S.E.
Techno-optimist	Scientific literacy (0-10)	1.1738**	.0690	1.1767**	.0695
	Exposure to AI (0-10)	1.1470**	.0600	1.0077	.2992
	Trust in science (0-10)	1.4958***	.1313	1.4109*	.2336
	Exposure to AI#Trust in science			1.0148	.0347
	Gender (ref. Man)				
	Woman	.5710*	.1584	.5705*	.1584
	Education (ref. Low)				
	Medium	1.1331	.4061	1.1178	.4019
	High	.8132	.3334	.7940	.3276
	Age (19-75)	1.0158	.0096	1.0157	.0096
	Constant	.0015***	.0016	.0024***	.0039
Techno-skeptic	Scientific literacy (0-10)	.8874**	.0413	.8908*	.0417
	Exposure to AI (0-10)	1.0169	.0499	.8480	.1930
	Trust in science (0-10)	1.0594	.0675	.9930	.1074
	Exposure to AI#Trust in science			1.0223	.0281
	Gender (ref. Man)				
	Woman	1.1481	.2689	1.1485	.2690
	Education (ref. Low)				
	Medium	.7140	.2003	.7258	.2037
	High	.7112	.2438	.7108	.2441
	Age (19-75)	1.0276***	.0082	1.0274***	.0082
	Constant	.1900*	.1412	.3129	.3066
Techno-phobic	Scientific literacy (0-10)	.8302**	.0592	.8138**	.0592
	Exposure to AI (0-10)	1.1028	.0821	2.6306**	.8693
	Trust in science (0-10)	.8290*	.0755	1.2621	.2225
	Exposure to AI#Trust in science			.8859**	.0397
	Gender (ref. Man)				
	Woman	.9313	.3355	.8895	.3277
	Education (ref. Low)				
	Medium	.5817	.2587	.5138	.2355
	High	1.2623	.6380	1.2777	.6532
	Age (19-75)	1.0218	.0128	1.0232	.0133
	Constant	.5414	.5704	.0297*	.0457
	N	500		500	
	R2	.0969		.1063	

Note: *p ≤ 0.05; **p ≤ 0.01; ***p ≤ 0.001.

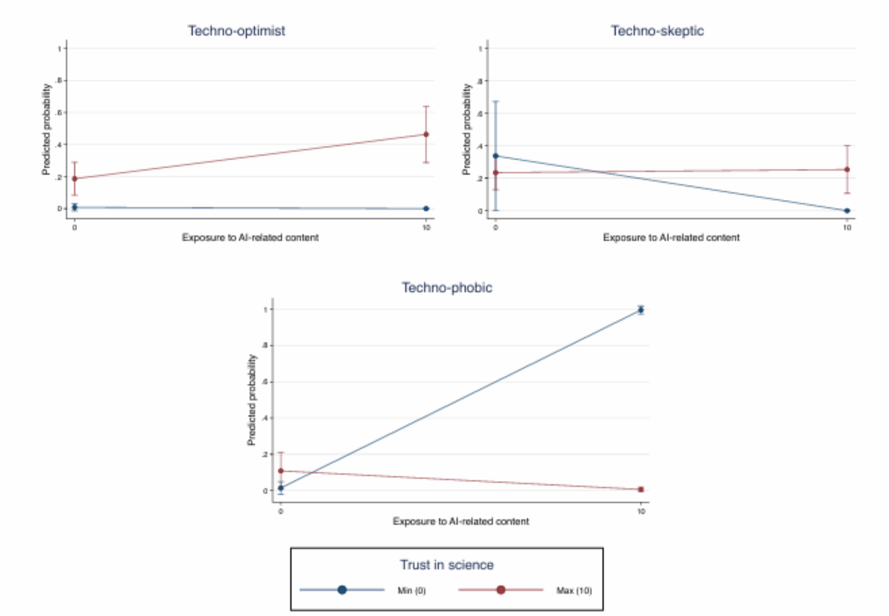
In M1, clear and systematic differences emerge across the latent classes. Membership in the techno-optimist class is strongly associated with higher scientific literacy (+17.4% per 1-unit increase), greater exposure to AI-related content (+14.7% per 1-unit increase), and higher trust in science (49.6% per 1-unit increase). While all three indicators affect the probabilities positively, trust in science has a significantly stronger impact. The effect of gender is also statistically significant. Indeed, women are 42.9% less likely than men to be techno-optimists. This aligns with previous research showing a persistent gender gap in attitudes toward technology, with men systematically expressing more positive views (Cai et al., 2017). Education and age, on the other hand, do not show significant effects.

The probability of becoming a techno-skeptic rather than being techno-ambivalent appears to be primarily driven by scientific literacy and age. Indeed, while trust in science and exposure to AI-related content do not have a statistically significant effect, a 1-unit increase of scientific literacy is associated with an 11.3% lower probability of developing techno-skeptical attitudes. Age is instead positively associated with this latent class. A 1-unit increase of age produces a 2.8% higher probability of being techno-skeptical – this means that a 50-year-old individual is approximately 88.3% more likely than an 18-year-old individual to belong to this category.

For the techno-phobic class, the effect of exposure to AI-related content remains close to 0 whereas scientific literacy and trust in science display a statistically significant negative effect. A unitary increase of scientific literacy is associated with a 17.0% lower probability (5.7 percentage points stronger than the effect observed for the techno-skeptic class) of being techno-phobic rather than techno-ambivalent. Similarly, a 1-unit increase of trust in science reduces this probability by 17.1%. Interestingly, unlike what was previously noted for the techno-skeptic class, age no longer has a statistically significant effect. This pattern suggests that while older respondents are more likely to develop skeptical orientations toward technology as frequently observed in previous research (Czaja & Sharit, 1998; Kubovics, 2025), the emergence of more radically anti-technological attitudes is not driven by age. This distinction underscores the importance of analytically separating skepticism from phobia, as they seem to be shaped by different underlying mechanisms.

Model 2 (M2) introduces an interaction effect between trust in science and exposure to AI-related content. The inclusion of the interaction term in M2 results in a modest but meaningful improvement in model fit, with the pseudo-R^2 increasing from .0969 to .1063, indicating that accounting for the conditional effect of AI exposure and trust in science adds explanatory power beyond the main effects alone. The previously discussed effects of scientific literacy, gender, age, and education remain largely unaltered. However, M2 reveals important differences regarding the effects of trust in science and exposure to AI-related content. To facilitate interpretation, Figure 2 presents their estimated marginal effects controlling for scientific literacy, gender, age, and education.

Fig.2 – Predicted probability of belonging to latent classes of attitudes toward AI as a function of exposure to AI-related content and trust in science (Model 2), estimated from weighted margins controlling for scientific literacy, gender, age, and education (Emilia-Romagna 2025, n = 500).*



* Note: the reference category is "Techno-ambivalent".

The predicted probabilities (see Figure 2) reveal distinct patterns in how trust in science and exposure to AI-related content jointly relate to latent class membership. For techno-optimists, exposure to AI has no effect on class probability once trust in science is held constant, whereas trust in science exerts a positive influence regardless of the level of exposure. For techno-skeptics, the relationship between trust in science and class membership depends on how much AI-related content respondents are exposed to. When exposure is low, trust in science appears to have no influence on the likelihood of being skeptical. However, at very high levels of exposure, trust in science begins to matter: respondents with higher trust in science are somewhat more likely to be classified as skeptical, suggesting that intense engagement with AI content amplifies the role of scientific trust in shaping cautious or critical attitudes toward technology. Finally, in the techno-phobic class, the interaction between trust in science and AI exposure is particularly pronounced. Among respondents with low trust in science, increasing exposure to AI content raises the likelihood of being phobic, whereas for those with high trust, exposure has no impact. Conversely, the effect of trust in science itself becomes more important at higher levels of exposure: when engagement with AI content is intense, respondents with lower trust in science are much more likely to exhibit techno-phobic attitudes. Overall, these plots illustrate that the effect of exposure to AI on class membership is conditional on trust in science, with the nature and magnitude of this moderation differing across classes.

Taken together, the results illustrate that attitudes toward AI are shaped by a combination of stable individual factors – such as scientific literacy, gender, and age – and more context-dependent influences, particularly the interaction between trust in science and exposure to AI content. While techno-optimism is largely driven by trust and literacy – in particular among men –, techno-skepticism and techno-phobia emerge in ways that depend on both cognitive resources and the degree of engagement with AI information. The differing patterns across latent classes underscore that negative orientations toward technology are not monolithic: skepticism appears more prevalent among older or moderately engaged individuals, whereas more extreme techno-phobic attitudes are strongly tied to low trust and high exposure. These findings highlight the importance of considering both individual predispositions and situational factors when analyzing public responses to technological change.

5. Discussion

The results provide strong support for H1, while offering partial and more nuanced support for H2. Consistent with H1, higher scientific literacy is positively associated with membership in the techno-optimist class and negatively associated with both techno-skeptic and techno-phobic profiles. In particular, scientific literacy substantially increases the likelihood of being a techno-optimist and significantly reduces the probability of belonging to the two more critical classes. Trust in science also plays a central role, especially in predicting techno-optimism, where it emerges as the most powerful positive correlate. Regarding H2, the moderation hypothesis is partially confirmed. The interaction patterns show that the effect of exposure to AI-related content is indeed conditional on trust in science, but this operates differently across profiles. Most clearly in line with expectations, among individuals with low trust in science, greater exposure increases the likelihood of belonging to the techno-phobic class, whereas this association disappears among those with high trust. However, for techno-skeptics, high exposure combined with high trust in science slightly increases the probability of skepticism, suggesting that exposure may foster more critical — rather than purely negative — orientations among scientifically trusting individuals. Finally, among techno-optimists, exposure has no effect and the likelihood of membership is affected by trust in science.

Overall, the findings indicate that scientific literacy consistently differentiates attitude profiles, while trust in science shapes how exposure to AI-related content translates into optimistic, skeptical, or phobic orientations.

Our findings confirm previous suspicions that exposure to information does not always lead to greater trust in technology. On the contrary, we showed that — among individuals with low levels of trust in science — an increase in exposure can negatively affect attitudes toward technology. This effect could be explained by a combination of at least three factors: 1) individuals who are already apprehensive about AI may experience an intensification of their concerns when exposed to high volumes of AI-related content; 2) it is possible that there is a substantive difference in the quality of the consumed media; 3) confirmation bias may also contribute to this pattern, as individuals with low trust in science might selectively attend to and internalize AI-related information that reinforces their pre-existing skeptical or negative views. The main point, however, remains that high exposure to science in the media does not significantly reduce skepticism or fears about AI applications. Therefore, our study confirms that a high level of information does not guarantee a positive attitude toward AI technologies.

At the same time, a higher level of information is associated with a stronger desire for stricter government regulation of AI, as well as with the belief that regulation should not be left solely to companies or scientists (Eom et al., 2024). Those who are more informed are also more likely to trust science and scientific institutions, suggesting a complex and non-linear relationship between information, trust, and attitudes toward technology.

We are, of course, aware of the limitations of our study. First, our measure of exposure to AI-related content captures frequency but not the nature or the tone of the information consumed. As a result, we are unable to distinguish between exposure to balanced, science-based reporting and exposure to sensationalist, alarmist, or misleading content. This constrains our ability to draw conclusions about the mechanisms underlying the observed relationships. Second, the analysis does not include measures of conspiracist predispositions or broader epistemic orientations, which may meaningfully shape both trust in science and reactions to AI-related information. Finally, we lack detailed indicators of respondents' socio-economic status. It is indeed plausible that individuals in more economically or socially vulnerable positions perceive AI as a greater threat to their livelihoods, which could partly account for stronger skeptical and/or phobic attitudes. It will therefore be important to further develop and articulate these findings through future national surveys and comparative research designs, in order to better capture contextual, psychological, and cultural variations.

In a period in which public authorities and administrations are increasingly implementing AI technologies in the workplace, in decision-making processes, and in local public services (Banfi & Pedroni, 2025), there is a growing need to adopt effective forms of citizen engagement in the governance of technology and innovation. Increased investments and efforts should be specifically devoted to comparative studies that investigate how carefully planned science communication relates to mutual trust among experts, citizens, and institutions, and more specifically to attitudes toward new technologies.

If media exposure to science does not fully explain the different attitudes toward AI technologies, then what does? Our results suggest that attitudes are rooted at a deeper cultural level, where values — such as trust — play a central role. Public awareness of AI is increasing, and the level of trust in science appears to be more important than other factors in explaining attitudes in this domain. We are aware, however, that higher levels of trust in science are consistently associated with higher levels of education, and that this relationship deserves further and more systematic investigation. This finding confirms the continued relevance of trust in science, which — beyond alarmist interpretations not supported by empirical data (Jamieson, 2018; Achenbach, 2015; Millstone & van Zwanenberg, 2000) — has become central to numerous research initiatives (Cologna et al., 2025), some of which are also funded by the European Commission[1].

According to our data, trust in science and scientists plays a crucial role in shaping both positive and skeptical attitudes toward new technologies. More broadly, our findings help to critically reconsider the role of trust in shaping citizens' attitudes and opinions toward an emerging technology such as Artificial Intelligence. Rather than dismissing public anxiety about AI as "just fear of technology", it is more productive to treat it as a vital feedback mechanism — an indication that it is necessary to step back, open up the conversation, and build stronger bridges between science, technology, and society.

6. Closing remarks

Overall, our findings confirm that attitudes toward Artificial Intelligence are structured along differentiated and internally coherent profiles, in which cognitive resources and relational variables interact in non-linear ways. Scientific literacy consistently reduces the likelihood of belonging to strongly

[1] For further information, see the POIESIS project website: https://poiesis-project.eu/.

negative profiles and increases the probability of techno-optimism. Yet, in line with interpretative approaches within Public Understanding of Science, knowledge alone does not fully account for attitudinal orientations. Trust in science emerges as the most robust and consequential predictor, shaping not only positive outlooks but also moderating how exposure to AI-related content translates into suspicion or anxiety.

The interaction effects identified in our models further complicate linear deficit assumptions. Among respondents with low trust in science, higher exposure to AI-related information increases the probability of techno-phobic orientations, whereas this effect disappears among those with higher trust. Information, therefore, does not operate as a universal antidote to fear or distrust. Rather, its impact depends on pre-existing relational dispositions toward science and expertise, or what authors such as Archer and colleagues (2015) have called "science capital". These findings resonate with international evidence showing that greater awareness of AI is often accompanied by more articulated expectations about oversight and accountability, including stronger support for public regulation and reluctance to leave governance solely to private companies or scientific elites (Eom et al., 2024; Pew Research Center, 2025; Eurobarometer, 2025).

Importantly, our data suggest that more informed citizens are not necessarily less critical; instead, they may demand clearer institutional safeguards and more transparent governance frameworks. In this sense, skepticism should not be interpreted merely as resistance to innovation, but as an expression of reflexive engagement within increasingly mediatized and politicized "social conversations around science" (Bucchi & Trench, 2021). The distinction between techno-skepticism and techno-phobia highlighted by our latent class analysis underscores that negative orientations are not monolithic: moderate critical attitudes appear linked to age and cognitive differentiation, whereas more radical rejection is closely associated with low trust and high exposure.

At the same time, we must emphasize the contextual nature of our evidence. The survey was conducted at the regional level, in the Italian Region of Emilia-Romagna - an area characterized by strong investments in digital infrastructures and scientific research. While this setting provides a particularly relevant laboratory for examining attitudes toward AI, the findings cannot be uncritically generalized to the national or international level. The patterns identified here should therefore be interpreted as analytically suggestive rather than statistically representative beyond the regional context. Future comparative and longitudinal studies will be necessary to test the robustness of these relationships across different socio-political environments.

In other terms, our results contribute to ongoing debates about the alleged "crisis of trust in science". Rather than pointing to a generalized erosion of confidence, they indicate that trust remains a central organizing principle in citizens' orientations toward emerging technologies. Public anxieties about AI should not be dismissed as irrational technophobia; they represent socially meaningful signals about expectations of fairness, accountability, and democratic oversight. Strengthening mutual trust between institutions, experts, and citizens - through inclusive governance and transparent communication - appears more promising than simply increasing the volume of information.

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