Promoting mystique, magic and the awe in the promotion and usage of AI products

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ABSTRACT
Smart technologies such as AI are developing and becoming a bigger part of everyday life. However, people don't always respond to AI based on what they know - but often on how these tools make them feel. This study builds on the work of Tully et al. (2024), which states that people with less technical knowledge of artificial intelligence (AI) can be more open to using it, since they see it as something magical or awe-inspiring. To explore whether this also applies in a diverse, international context, a survey with 121 students and staff at the University of Twente was conducted. The results confirmed the original finding: those who knew less about how AI works were more likely to view it as something fascinating and mysterious—and were more willing to embrace it. On the other hand, people who had a better grasp of the technology tended to be more cautious, especially when AI was used in roles that feel human, like making decisions or having conversations. Interestingly, when AI was used for more straightforward tasks, like sorting or calculations, technically knowledgeable participants were more receptive. Based on data analysis it was possible to identify that cultural background didn't seem to make a big difference in how people responded, suggesting that these reactions are universal and do not depend on cultural factors of nationality. This study not only validates, but goes beyond Tully et al. (2024) findings in for it shows that individuals do not accept AI only because they understand it, the sense of wonder the technology offers is also an important variable. For that reason, successful AI adoption may combine clear education with thoughtful, engaging communication about the technology.

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AI literacy, magical perception, technology acceptance, cross-cultural, mediation analysis

Declaration of own work

During the preparation of this work, the author used Claude in order to check the correctness of syntax and logic for data analysis. Chat GPT 3o model with deep search, to find relevant information considering given topic, Chat GPT 4o model, to create reference list, paraphrase specific grammatical constructions. After using these tools/services, the author reviewed and edited the content as needed and takes full responsibility for the content of the work

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1. Introduction

1.1 Background/Phenomenon

Artificial intelligence, which later will be shortened to the abbreviation "AI", is progressively incorporating into consumer goods and services, which is drastically changing the interactions between people and technology. The phenomenon in which AI products invoke mystique, magic, and awe among consumers is particularly interesting to observe, as it affects their receptivity and acceptance (Tully et al, 2024).

It is critical to analyze and investigate the link between AI literacy (understanding of artificial intelligence and existent scientific base of studies) and AI receptivity (the extent to which people are willing to use AI). Deeper investigation of these relationships may offer useful information to companies, designers, and legislators that want to more successfully promote the usage of AI technology in day-to-day operations. If people are more receptive to AI not because of understanding it, but because of emotionally captivation by it, then communication strategies, educational interventions, and ethical design approaches must account for this disconnect. This has implications for responsible deployment, public trust, and long-term societal impact of AI systems. This form of acceptance driven by emotional and symbolic perceptions rather than technical literacy is especially important because it challenges conventional models of technology adoption and reveals the psychological dimensions of trust in automation.

1.2 Research Gap

A literature study reveals paradoxical relationship between AI literacy and AI receptivity. In contrast to widespread opinion, new studies show that individuals with lower AI literacy have higher AI receptivity (Tully et al, 2024). These individuals are more likely to perceive AI technologies as magical, leading to feelings of awe that enhance receptivity Keltner & Haidt, 2003; Waytz et al, 2014).

Previous papers are mostly focused on situational and task-related factors impacting AI adoption, such as task objectivity, AI capabilities, and ethical concerns (Castelo et al, 2019; Longoni et al, 2019). However, comprehensive research on individual-level characteristics, such as AI literacy, is lacking. It creates a substantial gap in understanding how individual AI expertise systematically impacts adoption attitudes.

Other related research in disciplines such as consumer psychology and human-computer interaction show that anthropomorphic and magical ideas or perceptions of technology have a particular influence on its adoption (Epley et al., 2007; Kim & Sundar, 2012). This literature supports the hypothesis that increased emotional involvement and responsiveness, might be a result of a lower knowledge and so, the mystification of AI.

1.3 Purpose of the Study

The research by Tully et al (2024), demonstrated that lower AI literacy is associated with higher AI receptivity, and that this relationship is mediated by perceptions of AI as magical, especially among student populations, where emotional and anthropomorphic reactions to AI were more pronounced. Based on the described gaps and uncertainties in how AI literacy effects AI receptivity, the goal of this study is to experimentally evaluate the inverse correlation between AI literacy and AI receptivity among employees (professors, PhD candidates, student assistants, etc.) and students of varied foreign backgrounds at the University of Twente. The study especially investigates whether views of AI as magical moderate this link, and whether these effects differ by task type (human-like versus objective).

1.4 Research Question

This study builds on previous work of Tully et al (2024), by investigating if these findings hold up in an international academic context and whether nationality moderates the existing correlations. The study also aims to analyse if different task types (those with distinctively human-like vs. objective characteristics) alter how magical perceptions influence AI receptivity.

Summing it up, the main research question is the following: **To what extent does AI literacy influence AI receptivity, and is this relationship mediated by magical perception and moderated by task type and nationality?**
The sub-questions and arguments include:

- How does the perception of AI as magical mediate the relationship between AI literacy and AI receptivity?
- To what extent do task characteristics (distinctly human vs. objective attributes) moderate this relationship?
- To what extent nationality influence the strength or direction of these effects?

1.5 Hypothesis

Following the theoretical framework proposed by Tuly et al (2024) and presenting new variable as "nationality", the following hyphotesis were formulated:

H1: AI literacy is negatively associated with magical perception of AI.

H2: Magical perception is positively associated with AI receptivity.

H3: The relationship between AI literacy and AI receptivity is mediated by magical perception.

H4a: For objective AI tasks (sorting, calculations), higher AI literacy increases receptivity.

H4b: For human-like AI tasks (conversation, decision-making), higher AI literacy decreases receptivity.

H5: Nationality does not significantly moderate the relationships among AI literacy, magical perception, and AI receptivity in an academic setting.

These hypotheses were tested using mediation and moderation analysis based on the data collected from respondents exclusively from the University of Twente, namely students (Bachelors, Masters, PhD faculties), academic and administrative staff, (see Research Methodology section below).

1.6 Expected contribution

The study is expected to contribute to the academic understanding of AI adoption by investigating the paradoxical role of AI literacy. Adding the context of possible use-cases, the findings will guide marketers and educators in strategically using mystique and awe in AI products and services to improve or increase the process of adoption. Speaking of social implications, the findings may help to reduce the amount of mysticism and complexities, which are currently present around AI adoption, implementing more effective public engagement and education strategies.

2. Theoretical Positioning

This study uses consumer psychology and human-computer interaction theories, such as, anthropomorphism and awe, to analyze and find out how humans interact with AI. Anthropomorphism theory suggests that attributing human-like qualities to non-human agents, such as AI, increases emotional connection and builds trustworthy relationships, which in turn can boost technology acceptance or adoption, (Epley, Waytz, & Cacioppo, 2007). Awe theory describes how people respond to the perceived "magic" of sophisticated technology with amazement and openness, which can lead to the increased receptivity (Keltner & Haidt, 2003; Howlett & Raghunathan, 2023).

By explaining how magical thinking and emotional responses influence perceptions of AI, the main theoretical contribution advances consumer psychology. The idea of AI as both human-like and awe-inspiring elaborates on why people could accept technology they don't fully understand, particularly in low-literacy settings (Tully et al, 2024).

In addition, this study investigated if nationality factor influences this relationship, so, nationality would be treated as an important component. According to Müller & Voigt (2024) and Hofstede (2001), moral and cultural values formed by national identity impact how users anthropomorphize or in more simple terms perceive technology as living and thinking organism and feel awe. For instance, based on the studies of Müller & Voigt (2024) and Hofstede, (2001), users from collectivist cultures, for example, may be more driven to interact emotionally with AI and view it as socially integrated, meanwhile individualist cultures may more precisely take into consideration the control and autonomy factors, lowering both literacy and receptivity. The current study adds nationality into existing frameworks to analyze cultural variations in AI acceptance.

3. Methodology

3.1 Research Methodology

The research is using a quantitative, deductive methodology, which is designed to replicate and extend findings from Tully et al (2024), with a focus on nationality of student and university employees. A structured online survey was used to gather primary data from the students of the University of Twente, academic staff was also considered and included in a set of the respondents. The academic environment was chosen on purpose, since it provides knowledge-rich context, and the capacity to gather data on AI literacy and receptivity among educated population. In addition, highly internationalized student society in the University of Twente can assist with the investigation of nationality variable by analyzing how having distinct nationality may influence the AI acceptance and relationship between AI literacy and Receptivity.

Participants were recruited by group chats of students, personal connections with university employees and personal social media channels. For instance, LinkedIn, with useful tool as Alumni and sales navigator were used, to make sure that the respondents are exclusively from University of Twente. In order to restrict the reach of survey and make sure that only specific respondents can participate, the student or employee number was starting point in filling in the form. The ethical procedure of the University of Twente was taken into consideration and all of the personal data of respondents (student/employee numbers) was deleted once collected. Each participant hadto approve active non-anonymous online consent and had an option to opt-in and opt-out at any moment. With the help of these channels 121 respondents were gathered.

Speaking of the proportion of academic staff to students, an approximate initial ratio was estimated as 1:10 staff-to-student sampling ratio, based on the actual population at the University of Twente, which includes around 3,500 staff and over 13,000 students at the University of Twente (University of Twente, 2023). While Tully et al. (2024) did not define a ratio, incorporating staff in proportion provides a more comprehensive understanding of how various academic responsibilities connect to AI knowledge and receptivity. This approach is also supported by previous digital literacy studies that included both students and staff for comparative purposes (Hatlevik et al., 2015; van Deursen & van Dijk, 2016). Demographic characteristics such as age, gender, nationality, and educational background was gathered in order to conduct comprehensive subgroup analysis later in data analysis stage. However, the expectations considering student – employee ratio were not met, see Limitations.

Validated scales from Tully et al. (2024) were incorporated into the survey instrument to evaluate key variables of the research. Objective AI literacy was assessed using a standardized questionnaire that tests respondents' basic understanding of AI technology, (see Appendix B). This section of a survey contains simple questions to evaluate the awareness of people if for instance Spotify, TikTok or YouTube use AI in their recommendation system. AI receptivity was evaluated by participants' willingness to adopt and trust AI in various hypothetical scenarios. The respondents were asked to evaluate to what extent they can trust AI to perform certain task or take responsibility. Magical perceptions of AI was assessed through a scale designed to gain insights on respondents' anthropomorphic and mystical attributions towards AI technologies.

In order to standardize the survey, based on the study of Hilbert et al. (2016), it was decided to introduce the Likert's' or linear scale to questions, where the dichotomy may not fully represent the thoughts of participants, (Hilbert et al., 2016). The lowest point - 1 means "Strongly Disagree" and 7 "Strongly Agree".
After data collection, gathered information was analyzed with the help of statistical software, such as R and RStudio. Initially, descriptive statistics summarized the sample demographics and key variables. Inferential analyses - including correlation tests and multiple regression models then measured the relationships among AI literacy, magical perceptions, and AI receptivity, taking demographic factors and specifically "Nationality", as controlling. Lastly, nationality-based subgroup analyses was performed to find possible international differences in the studied relationships. According to Johnson et al (2020), nationality-based subgroup analyses are increasingly used to reveal how cultural values shape psychological outcomes, providing culturally insights, which may have different variations. Based on the study of He & Vijver (2023), nationality subgroup analysis is an important tool that can help to avoid overgeneralization in nationally diverse samples. However, these statements slightly contradict the final output, more on that in Results section

3.2 Research Process

The paper by Tully et al. (2024) plays a role of a guide for the research process, which systematically builds up from the literature evaluation and hypothesis generation to quantitative data collection and analysis using statistical mediation and moderation techniques. To validate and expand on current understanding of AI receptivity dynamics, theoretical frameworks from consumer psychology and human-computer interaction were integrated with empirical data, by conducting a survey in academic settings of University of Twente, (see Appendix B).

4. Results

4.1 Descriptive Statistics

During the data collection stage, 121 participants took part in the investigation, as summarized in Table 1. Majority of respondents were students (87.6%), with smaller groups of academic staff (5.8%), PhD candidates (5.0%), and administrative staff (1.7%). The gender balance was nearly even, with 52 identifying as female (43.0%), 68 as male (56.2%), and only one of the participants preferred not to mention that data.

Gender	Count	Percent
Female	52	43.0
Male	68	56.2
Prefer not to say	1	0.8

Table 1. Gender distribution

Speaking about Nationality factor, gathered sample was quite diverse, with the largest segments coming from Western Europe (35.5%) and Eastern Europe (32.2%), followed by Asian (9.9%), Southern European (6.6%), and South American (5.8%) origins, which is an indicator of an international academic community in university context

Key variables also showed rich variability and approximately normal distributions, supporting the suitability of collected data for further analysis. It was identified that the mean AI Literacy score was 2.63 (SD = 0.56), with a median of 3.00, ranging from 1.0 to 3.0. While this scale is more compressed than the 21-point scales sometimes used in the literature, its distribution is similar in both shape and central tendency to Tully et al. (2024), the paper of which reported mean literacy values near the center of the respective scales. Magical Perception averaged 3.60 (SD = 1.24, range: 1.0–7.0), and AI Receptivity averaged 4.25 (SD = 1.13, range: 1.5–6.67), both with near-zero skewness and low kurtosis, further supporting the appropriateness of parametric statistical analyses (see Table 2 for full details).

These descriptive results show that the current sample is broadly representative in terms of demographics and psychological diversity, with no evidence of floor or ceiling effects in the main variables. This strong variation and balance support the generalizability of the findings and allow meaningful comparison to Tully et al.'s larger-scale international samples.

4.2 Correlation Structure

The interrelations between AI literacy, magical perception, and AI receptivity in collected sample showed a pattern that matches the theoretical expectations and prior empirical research of Tully et al. (2024).

	AI Literacy	Magical Perception	AI Receptivity
AI Literacy	1.00	-0.31	-0.08
Magical Perception	-0.31	1.00	0.37

AI Receptivity	-0.08	0.37	1.00

Table 3. Correlation Analysis

It can be observed in Table 2, (see Apendix A, that the correlation between AI Literacy and Magical Perception was strongly negative (r = –0.31, p < .001), meaning that individuals with greater technical understanding of AI are less likely to view AI as
mysterious, or "magical." This replicates Tully et al.'s findings; their reported correlations between these variables range from –0.32 to –0.37 across diverse international and student populations, showing the stability of this psychological relationship.

Speaking about the relationship between Magical Perception and AI Receptivity, it was strongly positive (r = 0.37, p < .001; see Table 3), indicating that the respondents who view AI as magical or extraordinary are also more likely to express enthusiasm for adopting or using AI systems. Founded value closely matches with the research of Tully et al. (2024), where the range of 0.28 to 0.39 can be seen, again supporting the generalizability of created by authors theoretical framework. The direct correlation between AI Literacy and AI Receptivity was smaller and statistically non-significant (r = - 0.08, p = 0.36; see Table 3 for p-values), a finding that also fits Tully et al.'s results (- 0.10 to - 0.12 and not significant). This pattern suggests that AI literacy does not directly influence people's willingness to use or accept AI technologies but acts through its effect on magical perception.

Summing this part up, all correlations were in the expected directions, and the magnitude of these relationships in data closely matches those found by Tully et al (2024) across multiple countries, age groups, and sample types. Observing the same interconnection in multiple settings strengthens tin Tully et al.'s statement. It suggests that these patterns are not tied to one specific place or group but reflect a general way people think about AI.

4.3 Regression and Model Fit

The results of the multiple regression analysis showed similar output to the findings of Tully et al. (2024), which supports the core theoretical model, and supports the findings from the bivariate correlations. In the collected sample, AI Receptivity was regressed on AI Literacy, age, gender, and role, providing a comprehensive adjustment for potential demographic findings. Consistent with Tully et al.'s results, none of the demographic variables were statistically significant predictors of AI receptivity.

For example, the coefficients for all age groups, as well as gender and role categories, were non-significant (all p-values > 0.25). It can be observed that the relationships between AI literacy, magical perception, and receptivity are stable in different demographic subgroups and are not occasional outliers of sample composition, (see Table 5).

Predictor	**Estimate**	**Std. Error**	**t value**	**p-value**
(Intercept)	5.95	1.74	3.43	0.001 ***
ai_literacy	-0.16	0.20	-0.79	0.429
age18–24	-0.90	1.32	-0.68	0.497
age25–34	-0.95	1.29	-0.74	0.462
age35–44	-1.95	1.74	-1.12	0.265
age45–54	-1.78	02.01	-0.89	0.377
age55–64	-1.67	1.78	-0.94	0.349
age65 and above	-1.12	02.05	-0.55	0.586
genderMale	-0.01	0.22	-0.06	0.950
genderPrefer not to say	0.10	1.18	0.08	0.936
roleAdministrative Staff	0.15	1.19	0.13	0.898
rolePhD Candidate	-0.78	1.15	-0.68	0.496
roleStudent	-0.33	01.08	-0.30	0.763

Table 5. Regression Analysis

The regression coefficient for AI Literacy itself was negative (Estimate = –0.16, SE = 0.20), but statistically non-significant (p = 0.429). This replicates the findings of Tully et al (2024), results of which showed small, not impactful direct effects of AI literacy on AI receptivity once magical perception is controlled for. The non-significance of the direct effect in represented model supports the hypothesis of Tuly et al (2024), that the effect of literacy is primarily indirect - operating through its influence on magical perception rather than as a direct driver of receptivity attitudes.

Model fit values also closely parallel those reported by Tully et al. The R-squared value for the model was 0.029, indicating that only a small proportion of variance in AI receptivity is explained by the predictors included in the model including literacy and demographics, (see Table 6). This low explained variance is typical in psychological and attitudinal research, and is specifically mentioned in Tully et al.'s work, where R-squared values for similar models often range from 0.02 to 0.07. The residual standard error was also in line with prior findings, supporting the adequacy of the model for hypothesis testing, even if much variance in receptivity remains unexplained by these predictors alone.

Statistic	**Value**
Residual Std. Error	1.169
R-squared	0.029
Adjusted R-squared	-0.079
F-statistic (df = 12, 108)	0.267
Model p-value	0.993

Table 6. Model fit

Concluding that section of data analysis, these regression results confirm that the negative relationship between AI literacy and receptivity is not significant while a variable as magical perception present. Additionally, it also shows that factor of nationality is not playing a significant role in the creation of variance in AI attitudes. However, that can only be applied in academic context, more on that point can be seen in the Discussion section. This pattern further validates the focus on mediation (rather than direct effects) as the primary explanatory mechanism, and highlights the consistency of findings across different analytic strategies and samples.

4.4 Mediation Analysis

The mediation analysis provides compelling evidence that the effect of AI literacy on receptivity is largely, if not entirely, transmitted through the intermediary of magical perception, precisely as theorized by Tully et al. (2024). Using nonparametric bootstrapping (500 simulations), it was estimated that the Average Causal Mediation Effect (ACME)—the indirect path from AI literacy to AI receptivity through magical perception - and the Average Direct Effect (ADE)—the path from AI literacy to receptivity not explained by magical perception.

In collected data, the ACME was significant and negative (The result = - 0.23, 95% CI [- 0.45, - 0.08], p < .001), showing a consistent and reliable indirect effect. This means that as individuals' AI literacy increases, their perception of AI as "magical" decreases, which in turn reduces their receptivity to AI systems. This finding not only matches the statistical pattern described by Tully et al. but also closely aligns in effect size: Tully's studies commonly report ACME values in the range of –0.21 to - 0.27, always with high statistical significance (p < .001).

The ADE (direct effect) in the data analysis was not significant (Estimate = 0.12, 95% CI [–0.26, 0.53], p = 0.55), echoing the "indirect-only mediation" pattern repeatedly found in Tully et al. (2024). These findings suggest that when the pathway through magical perception is accounted for, there is no remaining direct effect of AI literacy on AI receptivity—supporting the idea that the influence of literacy is fully narrowed through changing how "magical" AI feels to people, rather than through other, unmeasured factors.

The proportion of the effect mediated was estimated at 2.03 in gathered sample, but with a wide confidence interval (-19.67 to 9.23). Although this specific estimate is imprecise—likely due to the relatively small sample size—the direction and implication are consistent with Tully et al., who generally find that the majority (often near or over 100%) of the total effect is mediated via magical perception. The wide interval here does not undermine the primary interpretation, if the t ACME shows significant and consistent values.

Collectively, these mediation results reinforce the central thesis of Tully et al.: the impact of AI literacy on people's openness to AI technologies operates almost entirely by demystifying AI - reducing the sense that AI is magical or incomprehensible, which in turn increases people's enthusiasm or worry. The clear replication of both the statistical and substantive findings shows the consistency of this mediational pathway and increases its theoretical and practical importance for future work in AI acceptance.

4.5 Moderation Analysis and Interaction Plot

In addition to the mediation, the research by Tully et al. (2024) claimed that context determines how AI literacy affects AI receptivity, namely the kind of activity that AI was used for. To examine this, the moderation analysis was conducted, aiming to visualize the interaction between AI literacy and task type (i.e., "human-like" vs. "objective" tasks) on predicted receptivity scores. Figure displays the results of this interaction analysis using an interaction plot.

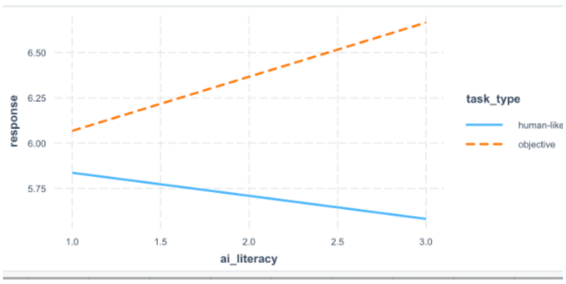


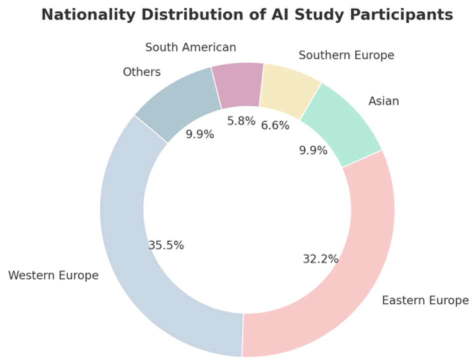
Table 8.

Discovered outcome revealed a typical crossover interaction, strongly aligning with Tully et al.'s most notable findings. Specifically, among participants evaluating "human-like" tasks (such as AI systems that mimic conversation or make subjective decisions), higher AI literacy is associated with lower receptivity to AI. In other words, as individuals' technical knowledge about AI increases, their willingness to accept AI in deeply social, interpretive or creative roles declines. This may reflect a greater awareness of the limitations, biases, or risks while using AI for such complex, person-like functions.
On opposite, for "objective" tasks (such as AI used for sorting, calculation, or other clearly defined rule-based activities), the effect reverses: higher AI literacy is associated with higher receptivity. Here, technical knowledge may help people to recognize where AI is reliable, efficient or potentially beneficial, leading to increased acceptance as literacy grows.

This crossover pattern – where the slope of the relationship between AI literacy and receptivity flips direction based on task type—is both statistically and visually striking, and directly mirrors the interaction plots and statistical findings presented by Tully et al. In that study, the moderation effect is consistent and statistically significant, demonstrating that the so-called "literacy penalty" (the idea that knowledge makes people more skeptical) is not universal, but rather appears in contexts where AI is tasked with human-like, not strictly functional, work, (see Table 8).
Concluding the results of moderation analysis, it can be observed that there is clear evidence that the effects of AI literacy are nuanced and depend on the context of AI application. This shows the importance of considering both the technological and the social dimensions of AI implementation – one of the key insights in Tully et al.'s theoretical model, and now successfully repeated in gathered during the data collection stage sample.

4.6 Nationality Factor

A notable strength of the current research is in its diverse, international sample. Unlike many previous studies that were draw mostly from single-country or single-culture samples, the respondents represent a diverse variety of nationality. While the largest groups hailed from Western Europe (35.5%) and Eastern Europe (32.2%), substantial numbers also came from Asian, Southern European, and South American regions(see Pie chart 1). Since the participants have different nationalities, the results are more likely to hold up elsewhere. This suggests that the psychological pattern identified by Tully et al. (2024), is not limited to a single culture but can be seen across various national backgrounds.



Pie chart 1.

Importantly, even with potential differences in educational systems, cultural attitudes toward technology, or socially accepted ideas about AI across national groups, the key relationships among AI literacy, magical perception, and receptivity were stable and statistically consistent across the sample. There was no evidence that nationality substantially changed the pattern of results, suggesting that the mechanisms identified by Tully et al. - the literacy-driven demystification of AI and its context-dependent effects on acceptance, may be psychologically universal, to the types of cross-national differences represented in this sample.
This stability in the results of nationality factor is particularly relevant in today's globalized technological landscape, in which AI systems are developed, and adopted across borders. The finding that AI literacy consistently shapes viewpoints by magical perception, not depending on nationality, shows a shared human behavior for public responses to AI - an insight that is both theoretically significant and useful in practice for policymakers, educators, and designers seeking to implement responsible and effective AI adoption around the world.

5. Discussion

The research is aiming to confirm (or reject) and extend the theoretical framework proposed by Tully et al. (2024), based on the results of conducted data analysis, particularly regarding the mediating role of magical perception in the relationship between AI literacy and AI receptivity, the final output matches with the findings of Tully et al (2024). The end result shows that individuals with lower levels of AI literacy (simply stating – individuals with lower amount of knowledge about AI) tend to perceive AI technologies as more mysterious or "magical". This finding supports hypothesis 1 (H1), which predicted a negative relationship between AI literacy and magical perception. This perception may significantly increase their willingness to adopt AI systems. That statement approves the H2, which suggested that magical perception increases AI receptivity. Important to mention, that the direct effect of AI literacy on AI receptivity was not statistically significant, supporting the idea that the emotional and symbolic perception of AI, rather than technical understanding alone, drives user enthusiasm and openness toward AI applications. This provides evidence for **Hypothesis 3 (H3)**: the relationship between AI literacy and receptivity is mediated by magical perception.

The moderation analysis provides certain nuances to this dynamic by highlighting the context-dependency of AI receptivity. Specifically, the study replicated the crossover interaction effect observed by Tully et al. (2024), showing that individuals with higher AI literacy are more receptive to AI in objective, rule-based tasks but less receptive when AI is applied to human-like, interpretive roles (creative, non-routine tasks). This pattern suggests that technical knowledge helps individuals to assess the positive use-cases and limitations of AI systems more accurately, providing trust in algorithmic reliability while triggering concerns and "healthy" skepticism toward the capacity of Artificial Intelligence to simulate human judgment or empathy. This pattern confirms the crossover effect predicted in **Hypotheses 4a and 4b**, showing that task type moderates how AI literacy affects receptivity. Drawing understandable conclusion, literacy does not simply increase or decrease receptivity in a linear way but interacts with task characteristics to shape user perception and behavior.
One of the key aspects of that research was to include "nationality" factor due to diverse pool of ethnicities in the population of the University of Twente. Even if taking into consideration the introduced "nationality" factor, the relationships between AI literacy, magical perception, and AI receptivity remained the same across the sample. There was no significant evidence to suggest that nationality moderated these effects. This finding shows that there is a certain degree of universality of human thinking process and how individuals respond to AI, even with completely different cultural context. It supports the idea that emotional and anthropomorphic responses to advanced technologies may be shaped by shared human cognitive processes rather than just taking into account the cultural differences, (Tully et al., 2024). Additionally, this result supports **Hypothesis 5 (H5)**, suggesting that nationality does not significantly moderate these relationships in an academic context.
Of course, the cornerstone of that study remains the same – replication and build up on Tully et al's investigation. However, it should be stated that other academic papers on the domain of AI with researching such factor as nationality or cultural differences exist. Recent work that compares respondents in different countries shows a clear pattern.

First, the study located in Germany and China (Brauner et al., 2024) found almost the same relationships as current study. Students who know less about how AI works often feel a stronger sense of "awe" and that feeling makes them more willing to use the technology.
Second, a 20-country poll by Ipsos (2023) confirms that basic excitement about AI jumps up and down from one nation to the next - India is leading in that aspect, while France is near the bottom - so local culture still may be a valid factor to use while assessing such relationships. That study contradicts the claim of current research
Third, the Vietnam-and-Singapore university survey (Roe et al., 2024) shows big gaps in how familiar students and staff feel with everyday AI tools. Those gaps match the spread in literacy scores that were found in gathered sample at the University of Twente.
Finally, an older USA-versus-South-Korea study (Im, Hong, & Kang, 2011) reminds that the usual technology-adoption factors such as ease of use or familiarity with technology - can work very differently across cultures.

Put together, these four studies can be summed up to universal conclusion, feelings of AI "magic" can be observed in different locations and cultures, even when everything else (language, education, local tech habits) is different. That repeating appearance validates the findings, that magical perception links low literacy to high receptivity
These findings may potentially have theoretical implications for different fields. In consumer psychology, they confirm the importance of affective drivers, such as awe and anthropomorphism, in shaping attitudes toward emerging technologies. In human-computer interaction research, the results support the argument that emotional perception and perceived mystique can have the same influence practical usability or efficiency in determining acceptance. From a cross-cultural perspective, the observed stable relationships across nationalities may challenge the assumption that the factor of nationality can be decisive in technology perception, at least in the case of AI in academic settings.
That research may have a variety of implications. For AI developers and designers, marketers, and educators, these results may give a hand in strategy creation, meaning that strategies focused solely on increasing AI literacy may be insufficient or even counterproductive if not combined with

efforts to manage the emotional perception of AI technologies. Providing transparency, especially in tasks requiring human-like reasoning, may to certain extent reduce or manage skepticism among more informed users. On the other hand, maintaining a perceived "magic" could be strategically beneficial in engaging users with lower levels of literacy, as long as it does not violate human rights or laws and ethical or moral side does not give unrealistic expectations. Meanwhile, the finding that task type moderates receptivity, can help in the creation of communication strategies, suggesting that these strategies should be tailored to the nature of the AI application being introduced, highlighting reliability and efficiency in objective tasks, while openly stating limitations and ethical considerations in socially interpretive contexts and human-like tasks.

6. Conclusion

The study shows that people's willingness to use AI is not shaped directly by how much individuals know about it. Instead, greater knowledge changes how "magical" or special the technology feels; that feeling, in turn, affects acceptance. The pattern also shifts with the kind of task involved. When AI handles human-like jobs (for e.g. as conversation or creative decisions), those who understand AI better tend to be more cautious. When AI performs clear, technical jobs (for e.g. sorting data or running calculations), those same knowledgeable users become more willing to rely on it. By confirming this pattern in an international group of students and staff, the study extends Tully et al.(2024) findings and shows that the "magic" pathway appears across different cultures.

Additionally, the results of conducted data analysis is showing, that the "Nationality" factor, in the academic environment, does not influence the correlation, the relationships are steady across highly educated individuals, even with diverse cultural background

6.1 Limitations and future research

However, there are a few limitations that should be mentioned for further researchers who may find that study useful. The relatively small sample size, though sufficient to detect mediation effects, reduces the precision of subgroup comparisons and limits the ability to state the conclusions about demographic influences. The academic settings may influence the generalizability of sample, since university members may have more access to and understanding of AI. Although the study used validated survey scales, self-reported answers can still be biased. Since all of the was collected at one point in time, the results suggest but cannot prove cause-and-effect links, even though the mediation analysis points to likely psychological pathways. The longitudinal or continuous studies should take place and investigate the problem further.

Future research should aim to take these limitations into consideration by increasing the sample to include broader populations and, what important to mention, in different sectors and educational backgrounds. Unfortunately, the initially stated sample size (200-250 respondents) was not reached, since the author underestimated the complexity of task, the analyzed sample contained 121 respondents. Continuous or longitudinal studies may provide deeper insight into how changes in AI literacy over time influence emotional responses and adoption behavior, since the body of AI literature will increase over time. Further investigations might also explore how personality traits, previous experience with technologies, or specific knowledge about studied domain can affect the mediating role of magical perception. Experimental designs that manipulate emotional framing or task context could offer stronger causal evidence for the mechanisms outlined in the current study.

Summing the limitations part up, this study may potentially contribute to a growing body of literature that highlights the complex relationships between cognition (the process of thinking) and emotion in technology acceptance. The findings sugest that people's feelings about AI depend not only on knowledge or in other words AI literacy, but on how that knowledge changes emotions, behaviors and perceptions. As AI becomes part of everyday life, understanding this link between facts (AI literacy) and feelings (AI receptivity), will be crucial for adopting the technology in ways that are ethical, useful, and fair for everyone.

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Appendices

Appendix A

Variable	**N**	**Mean**	**SD**	**Median**	**Min**	**Max**	**Range**	**Skewness**	**Kurtosis**
AI Literacy	121	2.63	0.56	3.00	1.0	3.00	2.00	-1.20	0.42
Magical Perception	121	3.60	1.24	3.60	1.0	7.00	6.00	-0.02	-0.58
AI Receptivity	121	4.25	1.13	4.33	1.5	6.67	5.17	-0.31	-0.06

Table 2. Descriptive statistics

Correlation Matrix with 95% Confidence Intervals

Variable	AI Literacy	Magical Perception	AI Receptivity
AI Literacy	-	-0.31 [,]	-0.08 [,]
Magical Perception	-0.31 [,]	-	0.37 [,]
AI Receptivity	-0.08 [,]	0.37 [,]	-

Table 4. Correlation Matrix with 95% of CI

Effect	Estimate	95% CI Lower	95% CI Upper	p-value	Significance
ACME (Indirect)	-0.229	-0.447	-0.076	< 0.001	***

Table

ADE (Direct)	0.116	-0.264	0.532	0.548	
Total Effect	-0.113	-0.492	0.286	0.592	
Prop. Mediated	2.027	-19.672	9.230	0.592	

7.

Mediation analysis

ACME = Average Causal Mediation Effect (indirect effect)
ADE = Average Direct Effect
Prop. Mediated = Proportion of effect explained by mediation
ADE = Average Direct Effect
*p < .001 (statistically significant)
Sample size used: 112
Simulations: 500

Nationality	**Count**	**Percent**
Western Europe	43	35.5
Eastern Europe	39	32.2
Asian	12	9.9
Southern Europe	8	6.6
South American	7	5.8
(… others …)	…	…

Table 9. Nationality distribution

Appendix B

10.1 Full R script (with short explanation):

```
# 0. Load Required Packages
install_if_missing <- function(pkg) {
  if (!requireNamespace(pkg, quietly = TRUE)) install.packages(pkg)
}
pkgs <- c("dplyr", "psych", "gt", "mediation", "interactions")
invisible(lapply(pkgs, install_if_missing))
library(dplyr)
library(psych)
library(gt)
library(mediation)
library(interactions)

# 1. Beautiful Descriptive Tables
nice_cat_table <- function(vec, name) {
  tab <- as.data.frame(table(vec))
  colnames(tab) <- c(name, "Count")
  tab$Percent <- round(tab$Count / sum(tab$Count) * 100, 1)
  tab %>%
    gt() %>%
    tab_header(title = paste(name, "Distribution")) %>%
    fmt_number(columns = "Percent", decimals = 1, suffixing = TRUE) %>%
    tab_style(
      style = cell_fill(color = "#E5E5CE"),
      locations = cells_column_labels(everything())
    )
}
nice_cat_table(data_clean$nationality, "Nationality")
nice_cat_table(data_clean$role, "Role")
nice_cat_table(data_clean$gender, "Gender")

# 2. Correlation Matrix with 95% CIs
ct <- psych::corr.test(data_clean[, c("ai_literacy", "magical_perception", "ai_receptivity")])
vars <- c("AI Literacy", "Magical Perception", "AI Receptivity")
r_mat <- ct$r
ci_low <- ct$ci.lower
ci_high <- ct$ci.upper
get_corr_ci <- function(i, j) {
  if (i == j) return("-")
  paste0(sprintf("%.2f", r_mat[i, j]), " [", sprintf("%.2f", ci_low[i, j]), ", ", sprintf("%.2f", ci_high[i, j]), "]")
}
tab <- matrix("-", nrow=3, ncol=3)
for(i in 1:3) for(j in 1:3) if(i != j) tab[i,j] <- get_corr_ci(i, j)
tab <- as.data.frame(tab)
rownames(tab) <- colnames(tab) <- vars
tab$Variable <- vars
tab <- tab[, c("Variable", vars)]
tab %>%
  gt() %>%
  tab_header(title = "Correlation Matrix with 95% Confidence Intervals") %>%
  tab_style(style = cell_fill(color = "#FDED9F"), locations = cells_column_labels(everything()))
```

```
#  3. Regression
reg1 <- lm(ai_receptivity ~ ai_literacy + age + gender + role, data = data_clean)
summary(reg1)

#  4. Mediation Analysis
# Group non-student roles for stability
data_clean$role_grouped <- as.character(data_clean$role)
data_clean$role_grouped[!(data_clean$role_grouped %in% "Student")] <- "Staff/PhDs"
data_clean$role_grouped <- factor(data_clean$role_grouped)

# Filter for non-missing values in all needed vars
data_med <- data_clean %>%
  filter(!is.na(ai_literacy),
      !is.na(magical_perception),
      !is.na(ai_receptivity),
      !is.na(age),
      !is.na(gender),
      !is.na(role_grouped))

# Remove levels with <5 obs for robustness
for (v in c("age", "gender", "role_grouped")) {
  tab <- table(data_med[[v]])
  keep <- names(tab[tab >= 5])
  data_med <- data_med[data_med[[v]] %in% keep, ]
  data_med[[v]] <- factor(as.character(data_med[[v]]))
  data_med[[v]] <- droplevels(data_med[[v]])
}

# Mediation regression formulas
form_m1 <- magical_perception ~ ai_literacy + age + gender + role_grouped
form_m2 <- ai_receptivity ~ magical_perception + ai_literacy + age + gender + role_grouped

m1 <- lm(form_m1, data = data_med)
m2 <- lm(form_m2, data = data_med)
med_out <- mediate(m1, m2, treat = "ai_literacy", mediator = "magical_perception", boot = TRUE, sims = 500)
summary(med_out)

#  5. Moderation Analysis (Interaction Plot)
# Make sure you have long-format data with columns: response, ai_literacy, task_type, magical_perception, age, gender, role

# If needed, re-level role for the plot as above:
long_receptivity$role_grouped <- as.character(long_receptivity$role)


long_receptivity$role_grouped[!(long_receptivity$role_grouped %in% "Student")] <- "Staff/PhDs"
long_receptivity$role_grouped <- factor(long_receptivity$role_grouped)

mod_tasktype <- lm(response ~ ai_literacy * task_type + magical_perception + age + gender + role_grouped, data =
long_receptivity)
summary(mod_tasktype)

interact_plot(mod_tasktype, pred = "ai_literacy", modx = "task_type",
        plot.points = TRUE, interval = TRUE, legend.main = "Task Type")
```

10.2 Survey Questions:

Consent

1. Do you agree to participate in this study?
(Yes / No)

Verification

2. Please enter your University of Twente student/staff number.
(Open field)

Demographics

3. What is your age?
(Under 18 / 18–24 / 25–34 / 35–44 / 45–54 / 55–64 / 65 and above / Prefer not to say)

4. What is your gender?
(Male / Female / Non-binary / Prefer not to say)

5. What is your nationality?
(Western Europe / Eastern Europe / Southern Europe / Northern Europe / Asian / African / North American / South American / Other)

6. What is your role at the university?
(Student / Academic Staff / Administrative Staff / PhD Candidate)

AI Literacy

7. Which of the following is a programming language commonly used in AI development?
(Phyton / HTML / Move / None of the above)

8. AI systems can independently make ethical decisions.
(True / False)

9. What does 'machine learning' mean?
(Learning patterns from data / Learning to walk / Learning to read) *(Multiple choice)*

10. Which of these applications uses AI?
(Spotify / Calculator / Microsoft Word / TikTok / YouTube Music) (Multiple choice)

Magical Thinking
11. AI can accurately predict human emotions based on facial expressions.
(Agree / Not sure / Disagree)

12. AI systems feel almost magical in their abilities.
(1–7 Likert scale: Strongly Disagree to Strongly Agree)

13. Sometimes, AI seems to think like a person.
(1–7 Likert scale: Strongly Disagree to Strongly Agree)

14. I find it hard to understand how AI works — it feels mysterious.
(1–7 Likert scale: Strongly Disagree to Strongly Agree)

15. AI often gives results that feel too smart to be real.
(1–7 Likert scale: Strongly Disagree to Strongly Agree)

16. Interacting with AI feels like engaging with a higher intelligence.
(1–7 Likert scale: Strongly Disagree to Strongly Agree)

AI Receptivity

17. I would trust AI to help write a personal letter.
(1–7 Likert scale: Strongly Disagree to Strongly Agree)

18. I would use AI to make suggestions for my mental well-being.
(1–7 Likert scale: Strongly Disagree to Strongly Agree)

19. I would follow an AI-generated career plan.
(1–7 Likert scale: Strongly Disagree to Strongly Agree)

20. I would rely on AI to sort and analyze financial data.
(1–7 Likert scale: Strongly Disagree to Strongly Agree)

21. I would accept an AI's recommendation on what route to take for travel.
(1–7 Likert scale: Strongly Disagree to Strongly Agree)

22. I would let AI automate parts of my online shopping experience.
(1–7 Likert scale: Strongly Disagree to Strongly Agree)

10.3 Cleaned survey data:

https://docs.google.com/spreadsheets/d/1Bl_tctyIV5w6YswBLKuwV9A5Y-S5PELt6k9zQfdrmL8/edit?usp=sharing