# AI Narratives: What Can They Tell Us About Individuals' AI Literacy and Emotional Attitudes toward AI Assistants?

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## Abstract

*How individuals understand Artificial Intelligence (AI) affects whether they can interact with AI assistants appropriately. To foster the appropriate use of AI assistants, individuals require realistic perceptions of what AI can or cannot do. However, perceptions (which we refer to as AI narratives) depend on individuals' AI literacy and their emotional attitudes regarding AI assistants. To investigate how literate individuals are and their emotional attitudes when dealing with AI assistants, we suggest developing a better understanding of their different AI narratives. Through a qualitative online survey, we explore differences in AI narratives among individuals with positive, ambivalent, or negative emotional attitudes regarding AI and among those with low, medium, or high levels of AI literacy. This work provides two research-guiding propositions on an individual's AI understanding and two recommendations for managing realistic AI perception-building.*

**Keywords:** AI narratives, AI perceptions, AI attitudes, AI literacy, human-AI interaction

## 1. Introduction

Recent developments in Artificial Intelligence (AI), especially through the growing maturity of Large Language Models (LLMs, such as GPT4), offer tremendous potential for individuals to become more efficient in daily tasks and job assignments (Benbya et al., 2021). Hence, the use of generative AI assistants for personal and work purposes is increasing (Dwivedi et al., 2023). With their ability "to perform cognitive functions that we associate with human minds" (Rai et al., 2019, p. iii), AI assistants possess greater autonomy and interactivity compared to earlier forms of digital assistants (Dwivedi et al., 2023; Maedche et al., 2019). These newer AI assistants, such as voice- (e.g., Alexa or Siri) and text-based assistants (e.g., ChatGPT or DALL-E), transform how individuals perceive and interact with them (Diederich et al., 2022; Dwivedi et al., 2023; Maedche et al., 2019).

Many individuals use AI assistants, but most do not adequately understand what it is with which they are interacting (Baidoo-Anu & Owusu Ansah, 2023; Dwivedi et al., 2023). The human-like behavior of AI assistants and their self-learning abilities (Dwivedi et al., 2023; Glikson & Woolley, 2020; Greene et al., forthcoming) can lead to misunderstanding, unrealistic perceptions, and misconceptions about what AI is, what it can do, and how it can be used (Diederich et al., 2022; Jordan, 2019; Willcocks, 2020). Individuals must develop realistic perceptions of AI (Diederich et al., 2022) to ensure that they interpret AI assistants' abilities correctly and, thus, use AI appropriately, that is, in a mindful and responsible manner that includes considering the possible negative consequences for society and the quality of life (Carolus et al., 2023; Kuzior & Kwilinski, 2022).

To develop realistic perceptions of AI, it is important to improve individual knowledge of AI assistants (Diederich et al., 2022). Individual's AI knowledge and the ability to understand and use AI correctly can be described with the concept of AI literacy, that is, the "new competencies [that] will be necessary in a future in which AI transforms the way that we communicate, work, and live with each other" (Long & Magerko, 2020, p. 598).

Beyond their literacy, individuals' emotional attitudes can lead to utopian or dystopian AI perceptions of AI and thus prevent them from using AI assistants appropriately (Cave & Dihal, 2019). Media and public discourse, with hopeful and frightening stories used to evoke the emotional attitudes of individuals, influence how individuals develop perceptions of AI (Cave & Dihal, 2019; Chubb et al., 2022). Research itself often "seem[s] to polarize around two storylines – hype or fear" (Willcocks, 2020, p. 287). This can result in individuals perceiving that "AI [will] become more powerful than humans" (Cave et al., 2019, p. 331). In short, both public and academic discourse can affect individual AI perceptions by triggering negative or positive emotional attitudes toward AI (Chubb et al., 2022).

To avoid unrealistic AI perceptions, research needs to understand how literate and emotional

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individuals perceive AI assistants (Diederich et al., 2022; Dwivedi et al., 2023). Individuals use narratives to express their perceptions of AI (Cave & Dihal, 2019), that is, stories through which they communicate and visualize their thoughts, feelings, experiences, and reflections (Schiff, 2012). Individual literacy, *what people know and think*, and individual emotional attitudes, *what people feel*, affect each other (Pinski et al., 2023). We expect both to influence AI narratives.

Research to date has focused mainly on dichotomous and collective narratives of "good" and "bad" rather than taking a more nuanced view of the "gap between dominant narratives" from an individual's perspective (Chubb et al., 2022, p. 1). We aim to explore differences in the narratives of individuals at various levels of literacy with AI assistants and with various emotional attitudes, following the call of Koukouvinou and Holmström (2022, p. 13) to further investigate differences between utopic and dystopic narratives. Our research question is: *How do AI narratives differ among individuals depending on their AI literacy and emotional attitudes regarding AI assistants?*

To answer this question, we conducted an exploratory qualitative study based on an online survey with open-ended questions. Exploratory research is appropriate, as it uses data for the "reconciliation of polyphonic narrative[s]" mainly based on inductive reasoning and explores insights (Sarker et al., 2018, pp. 764–765). We asked participants about their emotional attitudes toward AI assistants and their AI literacy to cluster them into similar groups. Within those groups, we explored their narratives inductively by asking open-ended questions about their views of AI and its impact. Following Sarker et al. (2018, p. 762), we used theoretical background on AI narratives, literacy, and emotional attitudes "up-front to guide the design and execution" of our exploratory study. Thereby, we aim to provide a more nuanced analysis of AI narratives to increase understanding of how and why AI perceptions might differ depending on individuals' emotional attitudes and AI literacy. We hope this will contribute to the understanding of what is required to foster individual development of more realistic perceptions of AI and thus help people interact with AI appropriately.

Next, we present the theoretical background, followed by the method. The results are then followed by the discussion. The paper ends with a conclusion.

## 2. Theoretical background

This section provides our theoretical background on AI narratives, literacy, and emotional attitudes.

### 2.1. AI narratives

Narratives are innumerable, as, by definition, all human forms of expression are narratives or can be treated as such (Czarniawska, 2009). Research often distinguishes between strictly negative and strictly positive narratives. The conditions of individuals' context, such as culture, media coverage, and education, may create a utopia in one context and a dystopia in another (Cave et al., 2019). AI narratives are highly polarized (Cave et al., 2019); with respect to AI, positive expressions often refer to hopes or utopias and negative expressions to fears or dystopias (Cave et al., 2019; Fast & Horvitz, 2017).

Table 1 introduces typical AI narratives that have been discussed in research to date; it follows the nine perception categories of Diederich et al. (2022, p. 100). For each category, we used an example from our initial literature screening within the AIS Electronic Library and Google Scholar, in which we searched for the following keywords: ("Artificial Intelligence") AND ("narrative*" OR "perception*"). We do not claim comprehensiveness in our work (Sarker et al., 2018); rather, we use "some theory … up-front to guide the design and execution" of our exploratory study (Sarker et al., 2018, p. 762).

**Table 1. Categories of existing AI narratives.**

| Category | Hopes | Fears |
|---|---|---|
| Perception (e.g., humanness) | "Humans merge with AI in a positive way, e.g., robotic limbs for the disabled, positive discussions about potential rise of transhumanism" (Fast & Horvitz, 2017, p. 964) | "Humans merge with AI in a negative way, e.g., cyborg soldiers." (Fast & Horvitz, 2017, p. 964) |
| Acceptance (e.g., usefulness) | "AI might make our day-to-day lives easier because we could ask computers to do more tasks for us." (Cave et al., 2019, p. 333) | "… an enlargement often results in [AI] solutions that are brittle and that become useless as soon as the application requirements change only slightly." (Weiss, 1999, p. 7) |
| Attitude (e.g., satisfaction) | "AI makes human work easier or frees us from needing to work at all, e.g., by managing ourschedules, automating chores via robots" (Fast & Horvitz, 2017, p. 964) | "AI displaces human jobs, e.g., large-scale loss of jobs by blue collar workers." (Fast & Horvitz, 2017, p. 964) |
| Per-formance (e.g., pro-ductivity) | "AI improves how [people] learn, e.g., through automatic tutoring or grading, or providing other kinds of personalized analytics." (Fast & Horvitz, 2017, p. 964) | "AI kills people or leads to instabilities and warfare through military applications, e.g., robotic soldiers, killer drones." (Fast & Horvitz, 2017, p. 964) |

| | | |
|---|---|---|
| Emotion (e.g., humor) | "AI might become the perfect friend, there to listen whenever we need and ready to meet our every desire." (Cave et al., 2019, p. 333) | "AI might cater to all our desires so well that we prefer AI interaction to human interaction." (Cave et al., 2019, p. 333) |
| Trust (e.g., risk, security) | "AI might help strengthen our military power because it could provide smarter weapons." (Cave et al., 2019, p. 333) | "AI might enable computers to become more powerful than us." (Cave et al., 2019, p. 333) |
| Learning (e.g., progress) | "From reaching human ability, it will move on to superintelligence in 2 years (10%) to 30 years (75%)" (Müller & Bostrom, 2016, p. 14) | "AI systems will probably (over 50%) reach overall human ability by 2040-50, and very likely (with 90% probability) by 2075." (Müller & Bostrom, 2016, p. 14) |
| Ethics (e.g., ethical behavior) | "AI enhances the health and well-being of people." (Fast & Horvitz, 2017, p. 964) | "AI lacks ethical reasoning, leading to negative outcomes, e.g., loss of human life." (Fast & Horvitz, 2017, p. 964) |
| Relation-ship (e.g., trust, responsi-bility) | "AI or expert systems help us make better decisions, e.g., when to take a meeting, or case-based reasoning for business executives" (Fast & Horvitz, 2017, p. 964) | "Humans lose control of powerful AI systems" (Fast & Horvitz, 2017, p. 964) |

This categorization of positive and negative expressions of narratives requires a more nuanced analysis given that AI perceptions of individuals in reality occur in mixed forms and can vary as a consequence of human-AI collaboration (Chubb et al., 2022). Hence, we aim to give nuance to these bipolar and dominant AI narratives by exploring possible differences between individuals' narratives depending on their different levels of AI literacy and emotional attitudes. We introduce this in the following, using the narrative categories in Table 1 to structure participants' responses deductively.

As argued in the introduction, previous research demonstrates that AI narratives are interrelated with AI literacy and emotional attitudes. "It seems that the perceived level of machine intelligence moderates not only the steepness of the trust trajectory but also the activities and psychological perceptions that lead to cognitive trust" (Glikson & Woolley, 2020, p. 638). While how literate individuals are can help in developing realistic perceptions in terms of *what people know and think*, and thus can enhance responsible and mindful use of AI through AI knowledge (Carolus et al., 2023; Diederich et al., 2022), individual emotional attitudes – that is, *what people feel* – can lead to perceptions overly utopian or dystopian perceptions of AI, preventing those individuals from using AI assistants appropriately (Cave & Dihal, 2019). This illustrates that AI literacy and emotional attitudes are highly interrelated (Pinski et al., 2023). Fostering AI literacy can help balance individuals' emotions and attitudes toward AI, which can motivate them to acquire further capabilities for using AI appropriately (Ng et al., 2021).

## 2.2 AI literacy

Beyond its use in the education context and its meaning with respect to the specific ability to read, literacy as we use it here comprises capabilities, such as knowledge, competencies, and skills, that are required for interaction and participation with other humans or artifacts (Barton, 2001). The concept of literacy has changed in light of technological progress (McLean, 2013), and "digital literacy" is often used to describe the capabilities required in individuals to decrease inequalities in the use of technology (Tapashi, 2018); this corresponds to the idea of literacy empowering people to create social equality. Gilster (1997, p. 1) introduced digital literacy as "the ability to understand and use information in multiple formats from a wide range of sources when it is presented via computers," after which many definitions followed.

AI-based technologies are "no longer always subordinate to a human agent, [as they] can now assume responsibility for tasks" (Baird & Maruping, 2021, p. 315) by acting with greater independence (Dwivedi et al., 2023). Current theories on literacy have become inadequate to account for this transformation in human-machine interaction and the relationships it creates (Leander & Burriss, 2020). In response, Long and Magerko (2020) introduced AI literacy as the competencies required to interact with AI successfully, and some conceptualizations of AI literacy followed in Information Systems (IS) research (e.g., Cetindamar et al., 2022; Ng et al., 2021).

While all these conceptualizations structure the relevant aspects of AI literacy in different ways, they have in common an emphasis on the increasing relevance of ethical abilities (e.g., judgment, critical thinking) that result from the greater autonomy of AI-based technologies and how this autonomy affects human-AI interaction (Baird & Maruping, 2021). Ethical abilities enable individuals to take account of ethical considerations with respect to AI, helping them better assess their own ethical perceptions, which are related to subjective moral values and norms, in the context of human-AI interaction (Ng et al., 2021). Hence, for realistic perceptions of AI and mindful use of AI (Carolus et al., 2023), individuals must also be aware of ethical considerations (Diederich et al., 2022). By conducting a systematic literature review and expert interviews, Pinski and Benlian (2023) conceptualized AI literacy and proposed a measurement instrument involving such ethical considerations. We used their measurement instrument to investigate the AI literacy of our participants, structuring them into groups based on possessing a high, medium, or low level of AI literacy so we could undertake a more detailed analysis of differences in their AI narratives.

### 2.3 Emotional attitudes toward AI

Attitudes are "a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor" (Eagly & Chaiken, 2007, p. 1). Research mainly discusses three attitude components for evaluation: the cognitive, affective, and behavioral components. Emotional attitudes, which are part of the affective component (Maier et al., 2019), can be characterized as beliefs or feelings that occur in a "mental state – conscious[ly] or unconscious[ly]" as settled opinions developed through cumulative experiences of individuals whose behavior is then influenced by those experiences (Altmann, 2008, p. 146). Experiences with AI can evoke emotional attitudes, which are often ambivalent, and can involve both "strong positive and negative evaluations at the same time" (Maier et al., 2019, p. 1). For instance, overestimation can lead to a perception of unfairness and thus evoke rather negative emotional attitudes (Hsu et al., 2021). We suggest that critical reflection concerning the pros and cons of AI and its output, which can result in different emotional attitudes, is necessary to develop realistic perceptions of AI assistants, given that trust can affect behavior and individuals' understanding of how AI acts compared to earlier technologies (Glikson & Woolley, 2020). We used the measurement instrument of Maier et al. (2019), which involves attitudinal ambivalence, and adapted it to our AI assistant context. We investigated participants' emotional attitudes to structure them into groups with positive, ambivalent, or negative attitudes for a more nuanced analysis of their narratives regarding AI assistants.

## 3. Method

This section provides methodological insights into our explorative study using a qualitative online survey. As stated in the introduction, exploratory studies can be used to inductively unify and structure narratives of qualitative data, which we acquired through a qualitative online questionnaire (Sarker et al., 2018). We used the concepts introduced in the theoretical background section to guide the development of survey questions and our data analysis. Below, we explain the sample, the questionnaire design, and the data analysis.

### 3.1 Sample

We chose several online channels to acquire participants from a variety of backgrounds to increase sampling quality (Brace, 2018, p. 1): via social media (35.62%); e-mail (18.72%); and crowdsourcing platforms such as Clickworkers (45.66%). This took place in February 2023. Given that our heterogeneous sample was acquired randomly through diverse channels, we adopted a convenient way to label our weakly defined group of survey participants (Leiner, 2014). We clarified to potential participants that the survey was about AI assistants and provided examples. Some 219 participants completed the questionnaire, of whom we used 151. We deleted data of participants who gave incomplete or invalid answers in the free text fields (n=12; e.g., by entering "…" or "no answer"). Further, we considered data only from participants with experience with AI assistants (n=25 were eliminated) and further confirmed their experience with at least medium- to high-level AI awareness (n=31 were eliminated).

The final sample comprises 58.28% male and 37.09% female participants (4.64% no answer) in the following age groups: 20–29, 27.81%; 30–39, 33.11%; 40 and older, 34.44% (4.64% did not answer). The highest level of education attained are as follows: high school degree, 22.52%; bachelor's degree, 16.56; master's degree, 31.79%; and 29.41% have other degrees, such as a PhD, or vocational training. Most of our participants, 66.89%, are professional workers; 10.60% are students; and 10.60% are freelancers; the remainder are retirees or did not provide an answer). Participants work in the information technology (IT) industry (13.25%); 8.61% in healthcare; 6.62% in education; 5.96% each in both finance and media; 5.30% in logistics; and 54.30 % in other industries (e.g., tourism, construction). Some 92.72% of participants completed the questionnaire in German and the remainder (7.28%) did so in English.

### 3.2 Questionnaire design

The questionnaire contains three sections. It begins by asking for demographic information; the first section also includes our first aptitude check, in the form of questions regarding the participants' experience with using AI assistants. We also asked participants to provide an example of the AI assistants they typically use. The second section comprises nine qualitative, open-ended questions (see Table 2), which we adopted from Laï et al. (2020) for the explorative analysis of AI narratives. Participants had already been told that the study concerned AI assistants, so we asked about AI in general in this section, rather than about AI assistants specifically. We did this to avoid participant bias and prompting them to think more broadly about "intelligence"; we wanted them to think about concrete assistants with which they had interacted without restricting their answers to those assistants.

**Table 2. Qualitative questions.**

| No | Question |
|---|---|
| 1 | How do you understand AI? |
| 2 | How would you describe the unique features of AI? |
| 3 | How do you understand Human Intelligence (HI) in comparison? |
| 4 | How would you describe the unique features of HI? |
| 5 | What associations do you make when thinking about AI? |
| 6 | Can you explain how your profession is or might be changing through AI? |
| 7 | What would be necessary to make you able to deal with AI successfully? |
| 8 | Is there a need to set limits on AI? Why or why not? |
| 9 | What impact can humans have on AI-based changes? |

The third section comprises the measures for AI literacy (from Pinski and Benlian, 2023) and emotional attitudes (from the medical context-specific items for strongly negative, mixed, and strongly positive attitudes of Maier et al. (2019, p. 9), but reframed to a more general context). We used these empirically validated measures to cluster our survey participants into groups of individuals with similar literacy levels and emotional attitudes. We also gauged our participants' AI awareness based on the measures for awareness of algorithm use in Dogruel et al. (2021). This was our second aptitude check, which eliminated 31 participants who did not exhibit at least medium-level AI awareness (see sample). To reduce the impact of noise in online surveys (Treiblmaier, 2011), all quantitative constructs were measured on a five-point Likert scale ranging from "1" (strongly disagree) to "5" (strongly agree). We further provided an "I don't know" option to avoid participants' guessing. We used Cronbach's Alpha (2001) to test reliability; all measures reached the critical level of 0.7 for internal constancy (Cho & Kim, 2015). This resulted in six groups of our participants (n=151) with similar AI literacy or emotional attitudes (see Table 3).

**Table 3. Groups of individuals.**

| | Emotional Attitudes | AI Literacy |
|---|---|---|
| Positive/High | n=23 (15.23%) | n=59 (39.07%) |
| Ambivalent/Medium | n=118 (78.15%) | n=31 (20.53%) |
| Negative/Low | n=10 (6.62%) | n=61 (40.40%) |

The questionnaire was provided in German and English. As all measures were in English, a group of bilingual personnel translated the German version to confirm correct grammar, spelling, and content comparability between English and German answers. Before issuing the questionnaire, we conducted a pilot study (n=11) to check understandability and clarify questions (Choy, 2014).

### 3.3 Data analysis

Given our exploratory research design, we followed inductive coding (Mayring, 2014, pp. 80–87). Table 4 is a snapshot of inductive coding.

**Table 4. Snapshot of inductive coding.**

| Quotes | Code | Category |
|---|---|---|
| "Imposing mandatory rules on AI would help prevent technology infringing human rights." I126 | AI infringes on human rights | In-humanity |
| "I hope the AI looks at the human and does not become a tyrant" I36 | AI should not endanger humans | |
| "AI cannot evaluate everything correctly because some things are also a matter of feeling." I41 | AI has no feelings | Lack of empathy |
| "Although AI systems can be very powerful, they still have limitations regarding their ability to understand human emotions, creativity, and empathy." I130 | AI struggles to understand human emotions | |
| "Especially for tasks that cannot be automated and are based on human values and emotions, the use [of AI] should be limited." I78 | AI should not conduct tasks that are based on human values | Lack of morality |
| "I have the feeling that decisions of AIs would perhaps correspond less to my values because they always rather follow a certain logic, but this is perhaps not always correct." I11 | AI may not always act according to our values | |

We deductively derived AI narrative categories from our theoretical background (see Table 1) to identify patterns regarding expressions of "hope" and "fear" (Mayring, 2014, pp. 95–98). All researchers coded the English-translated answers in Microsoft Excel. The coding quality was monitored throughout the process. We had several discussion rounds among researchers to scrutinize ideas on initial codes and to consider the results until a consensus was reached.

## 4. Results

This section presents the main findings of how AI narratives differ among individuals depending on their AI literacy level and emotional attitudes.

## 4.1 AI assistants in use

Most of our participants stated that they typically interact with text-based generative AI (88.74%); most mentioned ChatGPT. Participants using generative AI mainly demonstrated positive (15.67%) or ambivalent (77.61%) emotional attitudes. Their answers could be related to the narrative categories *acceptance* (19.84%) and *performance* (20.12%), based on the impression that AI will be a "relief from unloved administrative tasks" (I16) and is "making work easier, more efficient, and faster" (I19). They had either high (39.55%) or low (40.30%) levels of AI literacy. The remaining participants (11.26%) identified translation systems, social media algorithms, and voice agents such as Alexa or Siri as the AI-based technologies with which they typically interact. They rated themselves relatively low in AI literacy (41.18%), with ambivalent emotional attitudes (82.35%). This ambivalence can be seen in statements of participants' associations with using AI at work. One stated, "AI offers great possibilities for learning and progress, but I think as a result, many jobs will probably be lost" (I48) and can be related mainly to the narrative categories *trust* (22.50%) and *learning* (20.00%).

## 4.2 Sociodemographic differences

Younger participants (20–29; 26.49%) and participants older than 50 years (18.54%) showed a higher tendency toward positive emotional attitudes (n=23) compared to those ages 30 to 50, who demonstrated somewhat ambivalent emotional attitudes (40.40%, n=118). In most cases, the answers of younger participants can be related to the narrative categories *acceptance* (26.92%) and *performance* (24.04%). In contrast, the answers of older people demonstrated a broad diversification between all narrative categories. Female participants demonstrated positive emotional attitudes (25.00%), whereas male participants had more ambivalent emotional attitudes (82.95%). At the same time, predominantly female (46.43%) and older (53.57%) participants rated their level of AI literacy as low, while male participants' AI literacy scores were equally spread between low, medium, and high. Participants between the ages of 20 and 39 rated themselves as highly literate (52.38%). There are no significant differences with respect to participants' educational backgrounds. However, participants working in the IT industry tended toward negative emotional attitudes (11.26%) and rated their AI literacy level as either high (45.00%) or low (35.00%). In contrast, participants in other industries such as healthcare and logistics stated that they have high levels of AI literacy (47.17%) with a greater tendency toward positive emotional attitudes (18.87%).

Table 5 is an overview of the allocation of AI literacy and emotional attitudes within the narrative categories in Table 1. Participants with low AI literacy demonstrated relatively positive (22.95%) or ambivalent (73.77%) emotional attitudes. Participants with high AI literacy mainly showed ambivalent (83.05%) emotional attitudes (equal distribution between positive at 8.48% and negative at 8.47%).

**Table 5. Distribution of AI literacy and emotional attitudes within narrative categories**

| | n | AI literacy | | Emot. Attitudes | | Expression | |
|---|---|---|---|---|---|---|---|
| Per-ception | 38 | High | 39.47% | Positive | 18.42% | Hope | 18.42% |
| | | Med. | 18.42% | Ambival. | 68.42% | Neutr. | 57.89% |
| | | Low | 42.11% | Negative | 13.16% | Fear | 23.68% |
| Accep-tance | 73 | High | 52.05% | Positive | 17.81% | Hope | 97,26% |
| | | Med. | 15.07% | Ambival. | 76.71% | Neutr. | 02.74% |
| | | Low | 32.88% | Negative | 05.48% | Fear | 00.00% |
| Attitude | 9 | High | 66.67% | Positive | 44.44% | Hope | 66.67% |
| | | Med. | 11.11% | Ambival. | 55.56% | Neutr. | 22.22% |
| | | Low | 22.22% | Negative | 00.00% | Fear | 01.89% |
| Per-formance | 69 | High | 43.48% | Positive | 17.39% | Hope | 79.71% |
| | | Med. | 20.29% | Ambival. | 81.16% | Neutr. | 15.94% |
| | | Low | 36.23% | Negative | 01.45% | Fear | 04.35% |
| Emotion | 14 | High | 14.29% | Positive | 42.86% | Hope | 00.00% |
| | | Med. | 28.57% | Ambival. | 57.14% | Neutr. | 14.29% |
| | | Low | 57.14% | Negative | 00.00% | Fear | 85.71% |
| Trust | 30 | High | 13.33% | Positive | 23.33% | Hope | 26.67% |
| | | Med. | 13.33% | Ambival. | 70.00% | Neutr. | 13.33% |
| | | Low | 73.33% | Negative | 06.67% | Fear | 60.00% |
| Learning | 50 | High | 36.00% | Positive | 08.00% | Hope | 50.00% |
| | | Med. | 24.00% | Ambival. | 88.00% | Neutr. | 50.00% |
| | | Low | 40.00% | Negative | 04.00% | Fear | 00.00% |
| Ethics | 2 | High | 00.00% | Positive | 00.00% | Hope | 00.00% |
| | | Med. | 00.00% | Ambival. | 100.0% | Neutr. | 50.00% |
| | | Low | 100.0% | Negative | 00.00% | Fear | 50.00% |
| Relation-ship | 44 | High | 43.18% | Positive | 09.09% | Hope | 06.82% |
| | | Med. | 15.91% | Ambival. | 86.36% | Neutr. | 72.73% |
| | | Low | 40.91% | Negative | 04.55% | Fear | 20.45% |

## 4.3 Usage of narrative categories

Table 5 shows *acceptance* and *performance* are the most used narratives, with participants who are highly AI literate. Participants had neutral perceptions regarding AI within both categories, emphasizing that "we need to weigh whether the advantages of AI outweigh the disadvantages … we need to think about technology not only economically but also ethically" (I15). Participants with high AI literacy described the increasing use of AI at the workplace as a natural progression, and often mentioned that it required skill changes (33.15%), stating, for instance, "I think of a change in the world of work similar to what electricity brought in the last century. There will be new professions; some will change, others will remain. I see this as a normal evolutionary development" (I149). Hence, AI literate participants demonstrated realistic perceptions of AI assistants with AI narratives that balance AI's challenges and opportunities.

In comparison, answers related to the narrative categories *emotions, ethics,* and *trust* came from less-literate participants, who expressed fears by expressing views that AI "replaces the human workforce" (I14), "destroys humanity [like in the] movie 'Terminator'" (I12), represents "robots without compassion" (I134) or will lead to "dehumanization" (I69). Participants with a lower level of literacy felt AI to be dangerous for humanity because of its lack of sociability (impersonal, 5.43%) and saw AI at the workplace as replacing humans (19.02%). Moral and social deskilling concerns were raised, such as "I'm afraid we forget … how to thank!" (I36). These participants reported that they would need education to deal with AI (37.04%), as "for many people, AI is something supernatural" (I10).

While individuals with high AI literacy reported needing "lots of practice with AI systems to get the most out of them" (I151), fewer than 10% of participants with lower AI literacy reported needing practical training to improve their AI skills, instead insisting on "AI that works intuitively" (I121) and is "user friendly" (I111). Hence, participants with low levels of AI literacy used more negative expressions in their AI narratives, insisting that an artifact's design itself should improve human-AI interaction. It is notable that participants with lower AI literacy demonstrated more critical AI narratives (e.g., by criticizing the lack of morality of AI) than highly AI-literate participants.

## 4.4 Understanding of artificial and human intelligence

Participants with high AI literacy attributed cognitive intelligence mostly to AI (50.00%), describing human intelligence (HI) as multi-intelligent (44.44%). They described HI by using different facets of intelligence, including "empathy" (I7; emotional intelligence, 15.48%), "getting in touch with other humans to create community spirit" (I7; social intelligence, 9.52%), "moral decision-making" (I3; ethical intelligence, 4.76%), and "musically" (I26, creative intelligence, 9.52%). Participants with high AI literacy named features linked to intrapersonal (ethical, social, and emotional) intelligence as unique characteristics of HI.

In comparison, participants with low AI literacy described AI as more human-like (47.37%). For instance, one participant said AI is a system that "is supposed to imitate human intelligence or even better" (I100), and another described AI as "infallible, perfect, future-oriented" (I30). They expressed what were largely unrealistic expectations of how AI might change their profession (13.59%) or perceive that AI supports humans (28.80%). They did not restrict AI as cognitive intelligence and named few, if any, differences between AI and HI. Consequently, participants who are less AI literate seemed to lack a differentiated understanding of AI and HI. Even though they may employ more critical AI narratives, they seem to have more unrealistic perceptions of AI.

Looking at the understanding of AI versus HI, the findings suggest that participants with negative emotional attitudes defined HI based on the idea of multi-intelligences, using primarily ethical and emotional intelligence (55.55%). For instance, "people can make moral and emotional decisions" (I93) or "it is not only logical but also emotional and experience-based" (I20). Hence, participants with negative emotional attitudes may make more appropriate differentiations between AI and HI, while participants with positive emotional attitudes tend not to distinguish between the two in the same way.

Participants with positive emotional attitudes stated that AI could increase productivity or quality (8.33%) by attending to routine tasks (41.67%) and supporting humans (50.00%) – corresponding to the *acceptance* and *performance* narrative categories. Their associations regarding how AI affects their work were linked mainly to the fact that AI can support humans (28.80%). In comparison, those with negative attitudes often characterized AI as a trend (18.33%), such as a "hype cycle, as the value in the long-term is not clear" (I139), representing the *attitude* narrative. To use AI successfully, participants with negative attitudes (33.33%) and positive attitudes (45.83%) both wanted training and education to obtain, as one put it, "a better understanding of the function and limitations of AI" (I300).

## 4.5 Perceived human abilities to influence AI

The relevance of ambivalent emotional attitudes can also be seen in participants' answers regarding human influence on AI, given that all participants supported setting limits to AI's autonomy. Participants with positive emotional attitudes would prefer setting limits (79.17%), as they expressed fear of the adverse effects of unlimited AI capabilities. For example, one stated, "Yes, I believe that AI should not take over the important things of humanity, such as form part of weapons" (I57). Those with negative emotional attitudes also asked for limits on AI (66.67%) to prevent "military misuse" (I125) and "discrimination" (I63). Only one participant with negative emotional attitudes argued against limiting AI, stating, "Setting limits to science has historically never led to the improvement of society, so no limits should be set to AI" (I150). Individuals with ambivalent emotional attitudes wanted limits to protect humans (21.74%) and avoid a loss of human capital (19.57%), stating that AI is unethical (16.95%) and imperfect (8.70%), as well as limits that would maintain humans in control of and with responsibility for AI (25.00%). Hence, participants with ambivalent emotional attitudes demonstrated greater awareness of ethical issues arising from human-AI interaction – resulting in more critical AI narratives.

Irrespective of AI literacy level, participants agreed that humans should influence AI mainly through data input (21.93%); restricted usage (27.19%); discussing and adjusting parameters for AI models (27.19%); and through regulation (15.79%). No patterns emerged regarding the emotional attitudes of participants. However, participants with a relatively low level of AI literacy reported that humans have no chance of impacting AI (6.90%).

## 5. Discussion

In this section, we provide theoretical implications in the form of two future research-guiding propositions and two practical implications.

### 5.1 Theoretical implications: Realistic AI perceptions require AI literacy

Most of our participants demonstrated ambivalent emotional attitudes, which impact the ethical perceptions of individuals interacting with AI assistants (referring to the ethical narrative category). This aligns with Maier et al. (2019) and Glikson and Woolley (2020), who identified that ambivalent emotional attitudes and emotional trust strengthen the balance between the controversy over AI's and AI's challenges and, thus, critical reflection on AIs' impact. The high number of our participants with ambivalent emotional attitudes, coupled with the interrelationship between emotional attitudes and AI literacy described in our theoretical background section, suggest that AI literacy might be more adequate to explain differences between individuals who develop realistic AI perceptions and those who do not. Our results showed that people with high AI literacy demonstrated more realistic perceptions of AI by weighing pros and cons, whereas people with low literacy had more unrealistic narratives. Following Diederich et al. (2022), realistic perceptions also help bring ethical considerations to human-AI interaction. Thus, we propose:

***Proposition 1:*** *The higher the level of AI literacy, the higher an individual's ability to develop realistic AI perceptions.*

Participants with a low level of AI literacy seemed to have issues when it came to differentiating appropriately between AI and HI. Often, participants with low literacy could not distinguish unique features of HI and tended to attribute interpersonal intelligence (e.g., social and emotional intelligence) to AI. This can be linked to the increased autonomy and human-like behavior of recent AI developments (Dwivedi et al., 2023). AI-literate individuals have more realistic narratives. Hence:

***Proposition 2****: The more AI literate individuals are, the more realistic their narratives when differentiating between AI and HI.*

### 5.2 Practical implication: Responsible AI usage requires training

Our results highlight that AI-literate participants stated that they would require training to use AI appropriately; they saw the potential to improve responsible human-AI interaction through learning-by-doing (self-effort). Individuals with low AI literacy, in requesting greater usability, saw the potential for improving human-AI interaction within the AI artifact itself. This shows that management of the human interacting with the AI requires training for appropriate usage, just as management of the AI artifact requires developing appropriate design and implementation guidelines. This aligns with Heyder et al. (2023), who argue that thinking about ethical management of human-AI interaction requires considering both the AI and the human. "Ethical issues are particularly important [as] the inappropriate use of modern technologies can have certain negative consequences for society. Therefore, there is a need to disseminate models of proper responsible behavior and the use of these technologies for the benefit of people and increase their quality of life" (Kuzior & Kwilinski, 2022, p. 113). Therefore, our *first recommendation*, linked to AI literacy, is to align the management of both parts of human-AI interaction – the AI and the human – to ensure responsible use of AI. Irrespective of individuals' level of AI literacy or their emotional attitudes, education is important to understand AI's limits. This aligns with Ng et al. (2021, p. 9), who wrote that inclusive learning "bring[s] up future responsible citizens who are component in using AI in a reliable, trustworthy and fair manner, broadening participation in AI for everyone and ensuring inclusive AI learning."

In addition, there is a need for appropriate infrastructure and onboarding for AI assistants to foster inclusive participation. This points to one of the significant challenges of "how to design and develop inclusive AI for all" (Dwivedi et al., 2023, p. 9). Hence, to avoid a gap between individuals who can and cannot use AI appropriately, our *second recommendation*, linked to emotional attitudes, is to consider the context-specific requirements required for an inclusive human-AI interaction.

## 6. Conclusion

This study aimed to explore the differences in the narratives that individuals develop with respect to AI assistants depending on how literate and emotional they are, in order to provide a more nuanced analysis of AI narratives following the call of Chubb et al. (2022). We hope to increase understanding of what is required to foster realistic AI perceptions and help individuals interact with AI appropriately.

Corresponding to our research question, we determined that individuals with more positive emotional attitudes regarding AI assistants used positive expressions of narratives (e.g., hopes). Individuals with more negative emotional attitudes promoted more precise differentiations in narratives when comparing AI and HI. The study results further highlight that having an ambivalent attitude inhibits higher ethical awareness of possible issues when interacting with AI assistants that may contribute positively to the responsible usage of AI; this stands in contrast to those individuals who use AI efficiently for concrete tasks but do not consider possible biases and the moral consequences of usage. This supports the argument of Maier et al. (2019) for considering both the pros and cons of AI as part of acquiring the emotional attitudes required perceive AI realistically. Our results also demonstrate that highly AI-literate individuals have more realistic AI narratives. They described AI mainly as cognitive intelligence while using multi-intelligence to describe HI, with emotional, ethical, and social intelligence as unique features of HI. In comparison, less-AI-literate individuals did not exhibit many differences in their narratives when describing AI and HI, even though their AI narratives were rather critical.

The explorative design comes with some limitations. *First*, examining our propositions empirically by conducting a quantitative study would be essential to strengthen validity, especially with respect to possible interdependencies between AI literacy and emotional attitudes as assumed independent variables that might somehow be correlated. *Second*, our sampling could be enriched by valuable information regarding possible moderating effects of specific sociodemographic data, such as the ethical ideology of individuals, as we recognized recurring patterns in the qualitative data.

We hope our work provides valuable guidance for future research and practitioners on increasing understanding of the link between individuals' narratives and their AI literacy and emotional attitudes regarding AI assistants.

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