Emotional Responses to Artificial Intelligence Systems: A Systematic Review

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Abstract: With the growth in capabilities of Artificial Intelligence (AI) systems and their increasingly agent-like character, studying how humans relate to AI akin to social actors becomes highly relevant. A central aspect in this regard is how people respond to AI systems on an emotional level. This paper presents a systematic review of research on emotional responses to AI systems covering 10 years of research between 2015 and 2024. Based on a sample of 130 contributions, the review provides an overview of the field. It charts which domains and AI systems and which emotional constructs research has focused on and points to central findings regarding the antecedents and the consequences of emotional responses to AI systems. It furthermore examines how existing research has discussed implications of its findings for ensuring responsible AI use. Based on this comprehensive mapping of the field, the review points to gaps and limitations in existing research.

Keywords: affect, Artificial Intelligence, emotion, social cognition, survey data, systematic review

1. Introduction

What emotional responses do people show in their interactions with AI systems? This question becomes acutely relevant with the increasingly agent-like qualities of AI systems that can interact with humans in natural language and emulate conversations. Research on robotics has long been interested in people's empathy with embodied AI systems. In line with the hypothesis that there exists an "uncanny valley" (Mori 1970), research found that empathy with an anthropomorphized robot drops as the robot's appearance becomes humanlike without however achieving a lifelike appearance (Wang, Lilienfeld, and Rochat 2015). With more recent developments in AI applications emotional responses become more broadly relevant.

As Lee and See (2004, 76) noted already two decades ago, "[b]ecause automation and computer technology are growing increasingly complex, the importance of affect and trust is likely to grow". Their statement becomes especially relevant as people increasingly encounter non-embodied AI systems in various daily contexts (Huang and Rust 2021; Pantano and Scarpi 2022). More recent AI agents, such as more sophisticated chatbots, are based on Large Language Models (LLMs) and show a much increased capability to interact in the mode of language. The proliferation of such AI systems introduces a new category of social actors in people's lives (McKee, Bai, and Fiske 2023, 2). These artificial agents may also engender a greater variety of emotional responses when people interact with them. Consequently, the increasing capabilities of AI systems contribute to the relevance of studying an emotional dimension of AI systems and their interactions with humans. While research into emotional responses to AI agents is still relatively recent, it has quickly gained traction and led to the proliferation of empirical insights (Han, Yin, and Zhang 2023, 1307).

The present paper examines what is known about emotional responses to AI systems. Emotions are understood broadly as a set of interrelated responses that include neural, physiological, behavioral, and verbal mechanisms (Fox 2008, 16–17). Accordingly, we understand as emotional responses emotions that individuals feel in reactions to AI systems and people's AI system evaluations that involve an emotional dimension (such as empathy that people ascribe to an AI system). Emotions generally regulate people's conduct, which makes them relevant also for the conduct with AI systems and the trust that people place in them. Emotions can shape people's attitudes toward AI in ways that are partly separate from functional and instrumental aspects of AI systems – meaning that even if AI systems work well, they may still evoke negative emotions, such as discomfort (see, e.g., Rajaobelina et al. 2021). Or they might not work well, but still engender trust in them based on emotional mechanisms and shortcuts, e.g., through mimicking human and social qualities (see, e.g., Bai et al. 2024, 2).

Since AI systems can be deployed for many different purposes, the question of how people respond to AI systems on an emotional level is relevant for many areas of application, such as marketing (e.g., Pelau, Dabija, and Ene 2021), health care (e.g., Hsieh 2023) and education (e.g., Gao et al. 2024). This also means that the research is dispersed over different fields. This article takes stock of existing research on emotional responses to AI systems with a systematic review, focusing on research with quantitative survey methods. It does so with four main aims. It will, first, map *which emotional constructs* research has studied. Second, it will examine *other constructs associated with emotional responses*, both as independent and as dependent variables. Third, the review identifies *key empirical findings on relationships between emotional constructs and other variables*, as part of which it also ascertains to what extent contributions distinguish between an emotional and cognitive dimension or mechanism. Fourth, it discusses the *implications* of these findings for the challenge of ensuring responsible AI uses. The procedure for creating the review is based on the PRISMA protocol for systematic reviews. Based on a Scopus search and screening for relevance according to a list of inclusion criteria, the review examines 130 contributions over the period from 2015 to 2024 – which covers a major trend change of heavily increasing contribution numbers after 2020.

By mapping research on emotional responses to AI systems, this article advances existing research in three ways. First, it brings together and systematizes knowledge, showing which aspects have been extensively researched and where there remain gaps. These findings are also important in view of the ethical dimension of such emotional responses to AI systems, and thus hold important insights for responsible AI use. Certain AI applications may produce – necessarily inauthentic – emotional expressions that unconsciously trigger reactions typical of human interaction (Lv et al. 2022, 4). In this way they may engender emotional reactions that are manipulative through shaping people's behaviors against their deliberate, cognitive evaluations. Second, the insights from the systematic review are central to complementing models that are widely used to study technology acceptance. For instance, in the technology acceptance model (Davis 1989) and the unified theory of acceptance and use of technology (Venkatesh et al. 2003), emotions play a subordinate or no role. A likely reason for this is that these models are rooted in the theory of planned behavior and were designed for acceptance of technologies that people use like tools. Yet, AI systems are often less like tools and more like agents with whom people interact in less deliberate and conscious ways (Schepman and Rodway 2020). Reviewing research on emotional responses can point to ways in which technology acceptance research may need to go beyond traditionally studied factors. Finally, the systematic examination of emotional responses to AI systems has important implications for AI governance, particularly of potentially manipulative AI agents. Taking stock of emotional responses to AI systems offers critical insights that can inform balanced regulatory approaches.

The article is structured as follows. The second section presents the guiding questions of the review, followed by the description of the methodology in section three. Section four presents the analysis of the material and is the basis for the discussion in the fifth section. The article ends with a discussion that provides a summary and an outlook.

2. Research Questions

Systematic reviews are a formalized approach to assess the state-of-the-art within a research field in transparent and replicable way (Pollock and Berge 2018). While there exist guidelines for carrying out such reviews, the concrete objectives and the scope can differ. A review can narrowly focus on one specific relationship of interest and examine the distribution of effect sizes. Or it can serve to chart research in a given area and create a systematic overview. In the following, we adopt this latter broad perspective as our aim is to map the field of studies that deal with emotional responses to AI systems and systematize existing research. Four main research questions guide our review and also inform the methodological decisions described further below. Table 1 presents these research questions and the objectives we pursue with them.

Table 1: Overview of guiding research questions

Research question	Objective
RQ1: What emotional constructs has existing research focused on in the study of people's interactions with and perceptions of AI systems?	Provide an overview of the emotional responses that have been studied and examine their distribution.
RQ2: What domains and types of AI systems has existing research covered?	Examine what the main disciplinary interests are and what kind of AI systems are most commonly studied.
RQ3: What relationships between emotional responses to AI and other constructs have been studied and what are their key findings?	Chart which antecedents and consequences of emotional responses have been of interest thus far and what key findings research has accumulated about them. Examine to what extent studies distinguish between an emotional and a cognitive dimension or mechanism.
RQ4: What are the implications for responsible AI use?	Examine and discuss what existing research implies for responsible AI uses in line with ethical principles.

The systematic review for addressing the four questions has been based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines (Page et al. 2021). In the following, we describe the analytical protocol that structures the review and clarify the sampling strategy, the preparation of the material, and the analysis.[1]

3. Sample, data collection, and data preparation

3.1 Search strategy

For the search of studies on emotional responses to AI systems, we rely on a keyword search in Scopus. As a sample period, we chose the ten-year period ranging from 2015 to 2024. This decision assumes that the chosen sampling period is long enough to capture a trend break that marks a quickly rising interest in emotional responses to AI systems. As empirical studies on news articles about AI have shown an exponentially growing coverage in the second half of the 2010s (Sun et al. 2020; Korneeva et al. 2023), the specified search period is a good starting point for obtaining relevant studies since the occurrence of the trend break.

Since the systematic review focuses on available evidence regarding emotional responses to AI systems, it is limited to empirical studies. Further, the review only includes studies using standardized (i.e., not open ended) surveys with at least 100 observations (a minimum that offers a certain degree of reliability and generalizability). Surveys are widespread in empirical quantitative research and methodological similarity facilitates comparability across finding. The review covers artificial intelligence systems in general and thus includes non-embodied AI systems and embodied AI systems.[2]

[1] The approach and metadata of the systematic review have been registered on OSF and can be found at https://osf.io/cbt5p/?view_only=9c6ffba2d33049deb8899309303bc459.
[2] As our main interest is in non-embodied AI systems, as motivated at the outset of this article, we do not expressly search for embodied forms, such as autonomous vehicles or robots.

From these considerations, we derived a set of search terms (for the full search string, see Appendix A2). These include, as a *first* part, “artificial intelligence” and “algorithm*”. These key words lead to over-coverage because many studies may refer to them not as the subject of the research, but instead as the methods used in the studies. The broad search terms are nonetheless necessary to identify relevant studies and our search thus accepted many false positives in the sample.

Second, to narrow the search to empirical studies using survey data, the search terms also include “experiment”, “survey”, “*study” and “studies”. Third, since the focus is on individuals’ emotional responses as registered through survey studies, further keywords have been used to realize a more targeted search that is, however, still broad enough (“participants”, “respondents”, “subjects”, “reaction*”, “response*”, “attitude*”, “perception*”). As the aim of the systematic review is to provide a broad overview, we furthermore, fourth, used a broad set of disciplines that include computer science and engineering together with other disciplines that involve humans or interactions with humans as the subject of study: medicine, health professions, nursing, neuroscience, social sciences, decision science, economics, psychology, and the category multidisciplinary.

Finally, we presume that if a contribution is interested in the role of emotions in the context of people interacting with AI systems, it will generally mention “emotion” or closely related concepts in the abstract or keywords, since emotion is a firmly established concept. Although emotions are conceptually distinguished from affect, mood and other concepts involving affect, we also cover concepts closely related to emotions, such as mood or warmth. In this way we take into account that contributions do not always neatly distinguish between emotions and other, related constructs, and we opt for having over-coverage rather than under-coverage of relevant studies.

We refrained from using a list of all possible emotions such as anger, fear, and joy, which would have been too extensive and run into the obstacle of arriving at a unified, exhaustive, and authoritative categorization of emotions. The search did, however, use keywords regarding emotions that lie at a level of abstraction which falls between that of concrete emotions and the general term “emotion” (to consolidate the list of keywords for emotions, we conducted a systematic preliminary search in Scopus described in Appendix A1). Such keywords may be mentioned in the title or abstract without a simultaneous reference to “emotion” – which would lead to under-coverage of relevant contributions. The keywords used to cover studied emotional constructs are “emotion*” sentiment*, “feeling*”, “mood”, “empathy”, “warmth”.

3.2 Search and screening process

Based on the chosen keywords, we searched the Scopus database, using title, abstract, and keywords as the fields for the search and published articles and conference papers in English as the sources. For the period of 2015 to 2024, the keyword search in Scopus yielded 5,791 entries. This initial sample contained 13 duplicates. After removing these, one reviewer screened the remaining 5,778 entries for their general relevance based on their title and abstract. In this first step of screening, we excluded only studies that clearly did not study emotional responses to AI systems. For instance, AI systems designed to identify human emotions do not meet inclusion criteria. The evaluation of mere content generated by AI (such as artwork) – rather than of the AI systems themselves – was also not sufficient for inclusion. Contributions were identified for further screening when it was not clear from the abstract whether they empirically measured and analyzed emotional constructs, and/or whether they used standardized surveys. 466 entries remained as potentially eligible contributions after this first step (see Figure 1 below).

In a second step, two authors examined the abstracts and full texts of the articles to further narrow the sample using several exclusion criteria. These are substantive and methodological criteria that are based on our reasoning behind the search, as described further above, and were applied to the contributions (for details, see Appendix A3). The number of articles excluded based on each of the criteria is shown in Figure 1. After applying the exclusion criteria, the final sample contained 130 contributions (for a list of the included contributions, see Appendix A4).

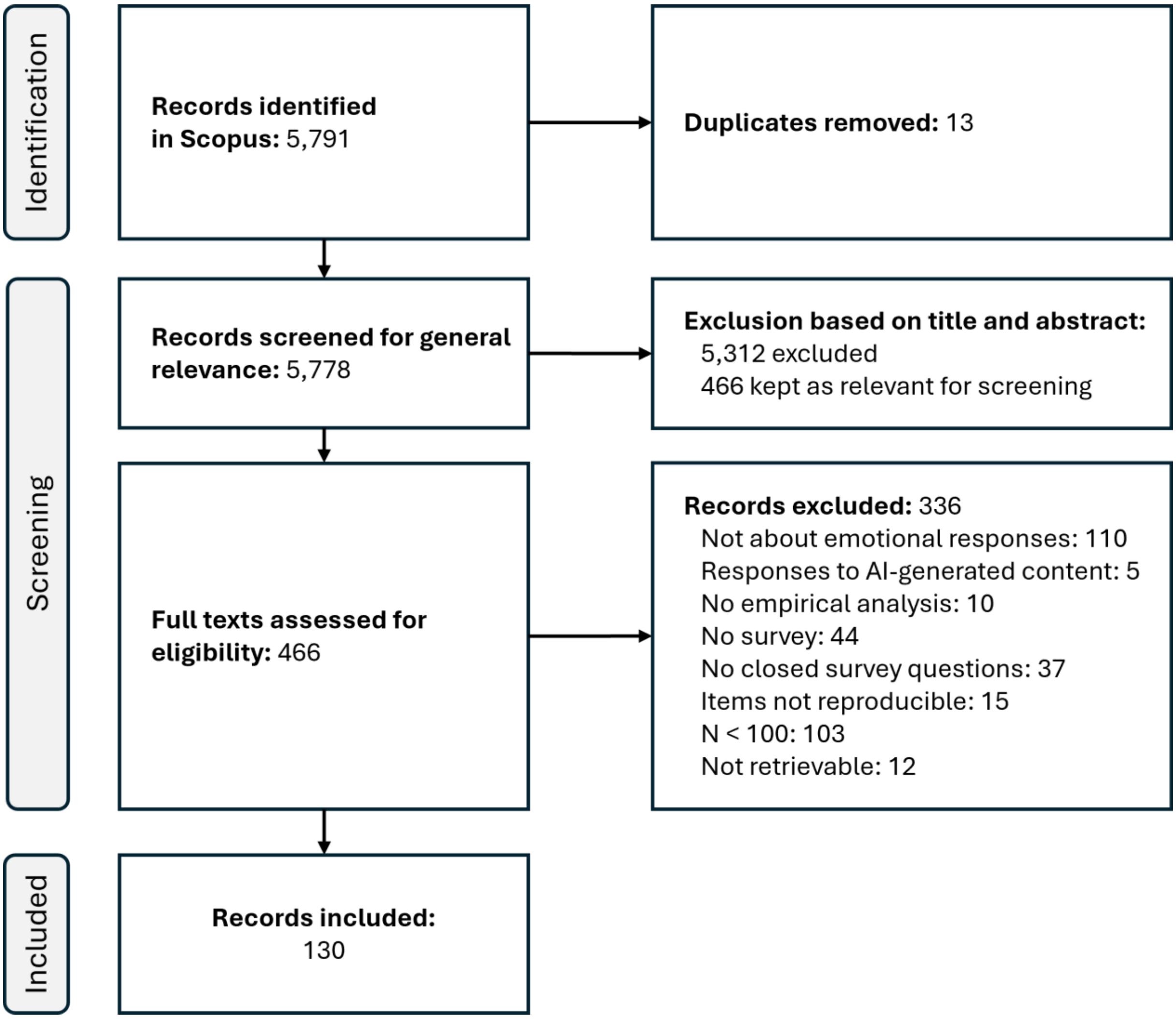

Figure 1: Overview of the document selection (PRISMA flow chart).

Figure 2 presents the resulting number of included articles per publication year. The graph shows a clear rise in frequencies in the year 2021. Based on the graph, the initial increase may already fall in the year 2018, with a dent in the years 2019 and 2020 that is likely due to the COVID-19 pandemic. In any case, the distribution shows a notable trend change within the chosen ten-year search period, which is very likely due to a surging interest in more recent advances and forms of AI systems. Our period selection can, therefore, be seen as a conservative choice in the sense that it even includes studies from a few years before the registered surge.

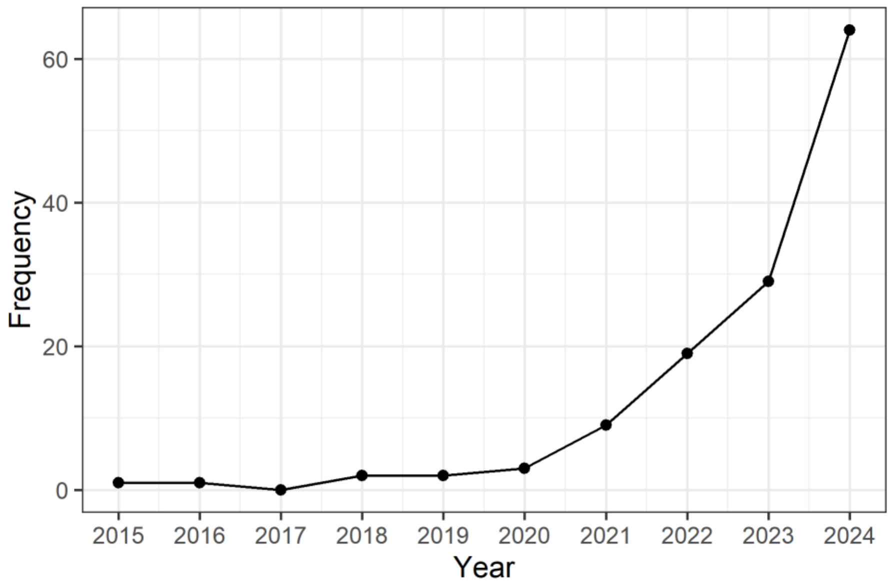

Figure 2. Distribution of the included articles over years.

3.3 Data preparation

We prepared our corpus for further analysis by creating categories to structure the material. The categories are derived from the research questions in Table 1 to capture patterns in the data that provide answers to these question. They are devised to be exhaustive with regard to the analytical framework. Detailed information on all categories and coding rules can be found in the codebook in Appendix A5. The coding was done by one of the authors, a second author assessed the categorization. Instances of perceived ambiguity or disagreement were resolved through deliberation, resulting in an update of the codebook to clarify the application of specific categories.

First, the *constructs for emotional responses* have been coded inductively. Two of the categories for emotional responses capture positive emotion and negative emotion, which are not specified further beyond their valence. Another category represents constructs for generic emotional responses that are of a general sort and are specified further. Under this category, we group constructs such as mood, emotional engagement, emotional trust, affinity, attachment, and love. Another group of constructs falls under warmth, which comprises constructs that are closely related to warmth, such as friendliness and social affability. The category empathy, in turn, refers to constructs that measure either individuals own' empathy or the perceived empathy or emotional intelligence of AI systems. Finally, we created various categories for concrete emotions such as joy, fear, and anger. Most of the constructs found in the reviewed contributions can straightforwardly be assigned to a category. However, sometimes contributions use different names for similar or closely related constructs, such as creepiness and eeriness, or emotional credibility effectively measuring perceived empathy. Details on which concrete terms in the included contributions are grouped under which category in the analysis can be found in Appendix A5.

Second, the *domains* in which the studied AI systems were deployed have been inductively coded. These categories are mostly straightforward, e.g., for health, education, finance and banking, e-commerce/retail, and the hospitality sector (i.e., travel, hotels, and restaurants). One of the categories is reserved for generic or unspecified AI use, e.g., when studies examine how people generally respond to a chatbot or investigate how the public evaluates AI in general. We also created a category "other" for rare and very narrow applications such as AI systems used in charity and for mourning (resurrection technology).

The *types of AI systems* studied have been grouped using the following inductively created categories. (a) general or unspecified references to AI, (b) virtual agents of different kinds (e.g., chatbots and other generative AI systems), (c) robots and automated vehicles (including service robots), (d) recommender systems, (e) automated decision- or scoring systems, (f) emotion analytics applications, (g) strong AI (i.e. artificial general intelligence that does not yet exist), and (h) surveillance tools. While technically more fine distinctions are possible, the descriptions of AI systems are not generally as detailed as would be needed to consistently and reliably make more fine-grained distinctions.

Third, the included contributions study a variety of associations between the emotional constructs and other constructs, such as intention to use or satisfaction with an AI system. These *associated constructs* have been categorized inductively and depending on whether they appear in the analyses as *independent or dependent variables*. Based on our coding, six groups emerged. These are (a) behavioral dependent variables and (b) evaluations of AI systems as dependent variables. Among independent variables, we created categories for (c) the contrast of AI versus no AI, (d) features of AI systems, (e) respondent characteristics, and (f) tasks and domains.

Fourth, we coded contributions with regard to whether they discussed the importance of *distinguishing an emotional dimension from a cognitive dimension* in people's perceptions of AI systems. This is the case, for instance, if a contribution emphasizes that besides cognitive evaluations like reliability of an AI system, there are also emotional reactions to an AI system that are a separate mechanism through which people forms attitudes toward the system. Finally, based on the discussion and conclusion of the reviewed contributions, we coded whether a contribution discusses the implications of their findings specifically for responsible AI use. This category is directly based on the fourth research question stated further above in Table 1. The category reflects *whether the findings of a contribution are discussed in terms of ethical issues* *and/or social values* – and is coded as "yes" in that case. It is not enough for a contribution to merely mention ethics without spelling out how the findings relate to ethical considerations.

4. Analysis of the Material

4.1 Publications by domains and AI application

Looking at the domains in which the reviewed contributions study emotional responses to AI, the category marketing, e-commerce, retail leads the list shown as in Figure 3. Emotional responses to AI systems are of major interest in the context of applications designed for interacting with users as consumers. A similar interest is also present in studies that examine AI systems in hospitality and tourism and in finance and insurance, which together make up about the same share as the most frequent category. Other frequent categories are health, work, and education. Particularly the large share of studies dealing with applications in health care attest to a major interest in AI systems that support medical staff or directly interact with patients, and in the emotional responses that this involves. It is notable that education and especially government uses are covered much less, although these are highly sensitive domains in which emotional manipulation can be severe.

Turning to the kinds of AI systems examined in the contribution, there is a clear concentration on virtual agents, such as chatbots or simulated agents. Recommender systems and automated decision-making systems, in contrast, are of marginal relevance in the reviewed sample of contributions. The focus thus clearly lies on AI systems designed for people to directly interact with. Some of the contributions also study robots, such as service robots, and automated vehicles, but they make up only a small share. The same is true for the category general AI.

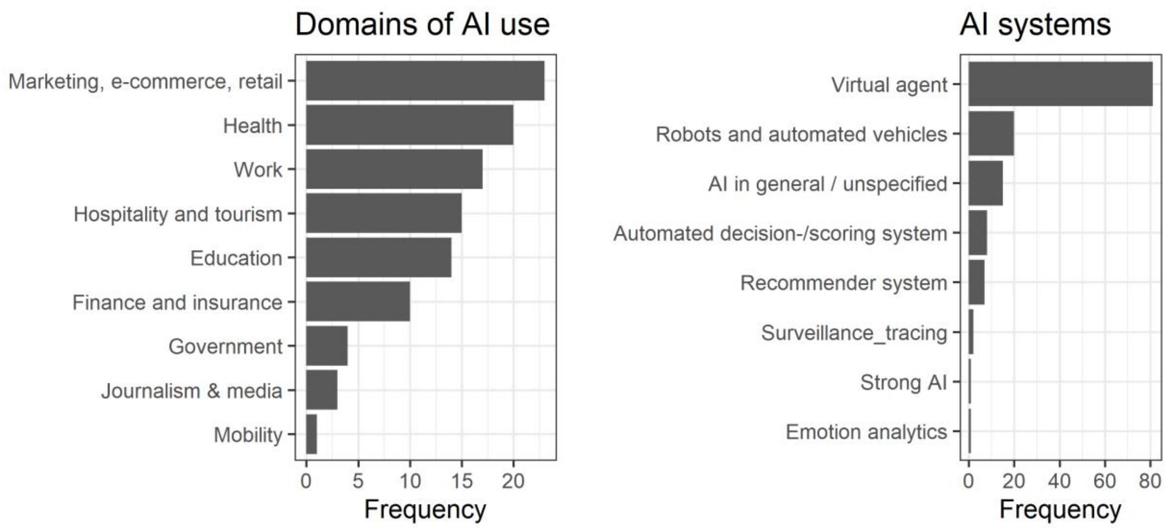

Figure 3. Number of contributions by domain and AI system.

4.2 Emotional constructs

The reviewed contributions study a broad range of emotional responses. Their frequencies in the sample also vary considerably. Figure 4 presents the emotional constructs with a frequency of at least five (note that more than one construct can be covered in a single contribution).[3] Three constructs stand out in terms of the frequency with which they have been covered. With a share of about a third of all contributions, empathy is the most studied emotional construct. It comprises perceptions of empathy or emotional intelligence of AI systems as well as respondents' own feelings of empathy. Generic measures of emotions and perceptions of warmth are each covered in about a quarter of all included contributions. Measures of positive emotions and negative emotions are also regularly covered in the sample, although less frequently than the three most frequent categories.

The constructs following the five most frequent categories are all discrete emotions (including the ones not shown in Figure 4), with enjoyment, fear or anxiety, emotional

[3] For the entire list and frequencies of covered emotions, see Appendix A6. Appendix A7 furthermore documents the distribution of the number of items used to measure the constructs shown in Figure 4.

creepiness, and discomfort being the most frequent of them. Emotional creepiness stands out among these concrete emotional reactions as it is less commonly known than, e.g., joy or fear. Langer and König (2018, 3) describe emotional creepiness as “a rather unpleasant affective impression elicited by unpredictable people, situations, or technologies”. It is thus a negative emotion that is closely related to the perception of uncanniness of AI systems.

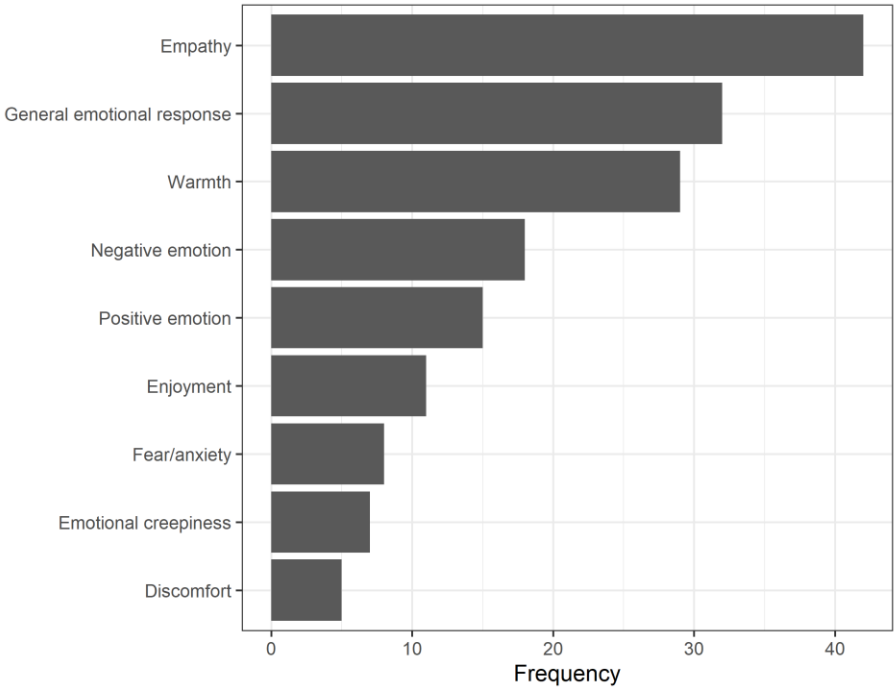

Figure 4: Frequencies of emotional constructs examined in the sample. Only categories with at least a frequency of five are shown.

4.3 Overview of the antecedents and consequences of emotional responses

Figure 5 shows the frequencies with which the contributions in the sample cover different kinds of dependent variables – *i.e.*, variables influenced by emotional responses. The figure distinguishes (1) behavioral variables and (2) attitudinal variables. As the figure shows, behavioral variables are more frequent, especially due to the prevalence of variables that reflect use or intention to use AI systems, such as continued use or loyalty intention. Other constructs repeatedly used as dependent variables are readiness to spend money and recommend an application or service, but also the expressed readiness to cooperate with or to object to the use of an AI system.

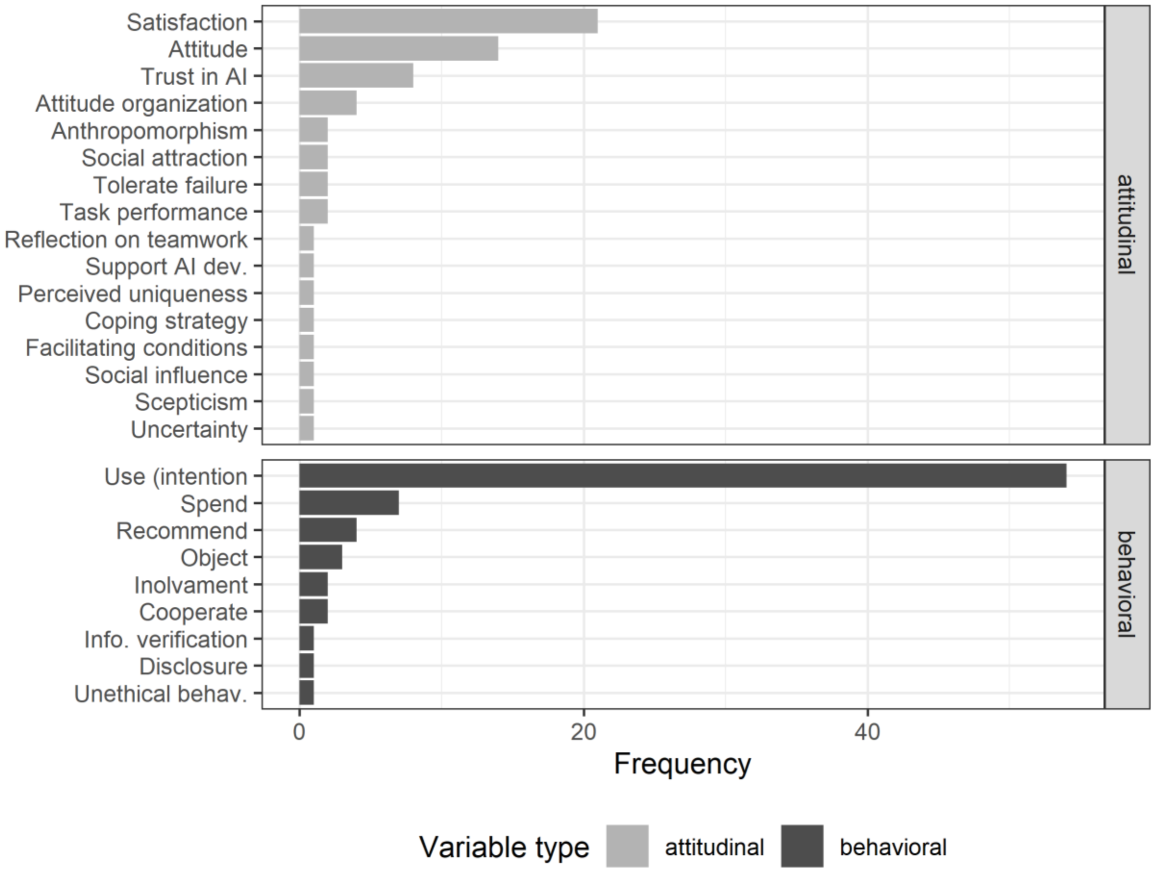

Figure 5: Frequencies of dependent variables

Among attitudinal constructs used as dependent variables, measures of satisfaction are the most frequent, followed by general attitudes toward AI, trust in AI systems, and attitudes toward the organization deploying an AI system. Overall, emotional constructs feature as an *independent* variable that leads to subsequent outcomes in 89 of the 130 contributions in the sample. This number is slightly lower than the number of contributions with emotional constructs featuring as the *dependent* variable.

Looking at the constructs that have been examined as causes or predictors of emotional responses, there is again a notable concentration on a few constructs, as shown in Figure 6. The figures distinguishes between (1) AI system features, which also includes the contrast of AI use versus no AI use (e.g., a human), (2) respondent features, and (3) the task or domain of AI system use.

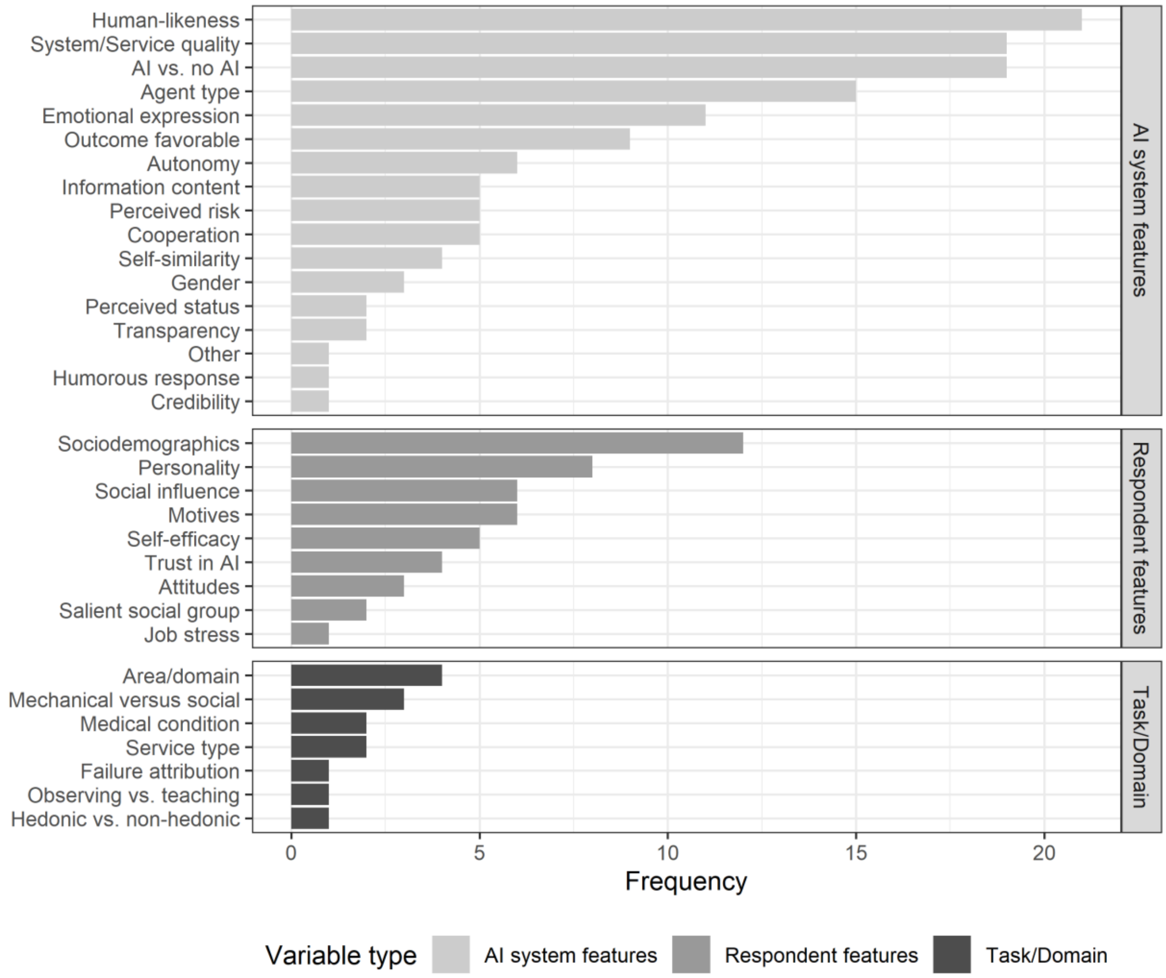

Figure 6: Frequencies of independent variables

AI system features are clearly the most frequent group of independent variables in the covered contributions. There is a predominant interest in features that concern the agent-like nature of AI systems, i.e. their human-likeness, emotional expressions, autonomy, cooperativeness, and the agent type, which comprises, e.g., different forms of intelligence. This is striking as it indicates a major concern of existing research with the possibilities to employ AI systems in ways that substitute for humans and with the question how people feel about this. Yet, given this interest in the role of agent-like qualities, it is equally striking that an explicit contrast between AI systems and humans is only included in less than one fifth of all studies in which emotional constructs are a dependent variable (19 of 104).

Other features that have been studied repeatedly are perceptions of the quality of an AI system or of the service it provides, the favorable versus unfavorable outcomes of AI system uses and perceived risks tied to an AI system. The remaining AI system features shown in Figure 6 all have frequencies below five. Notably, although transparency is an important predictor in research concerned with trust in AI as the dependent variable (Glikson and Woolley 2020), it is rarely studied as an antecedent of emotional responses.

The independent variables that fall into the remaining two groups – respondent features and tasks or domains – are much less frequent. Several respondent features are covered by at least five contributions in the sample. Among them, sociodemographic attributes are the most frequently studied, followed by personality (e.g., extroversion or neuroticism), motives, perceived social influence, and self-efficacy. Finally, the examined contributions rarely cover and compare different tasks or domains. The most frequent are distinctions between concrete domains in which AI systems are deployed and a contrast between tasks involving mechanical problem-solving versus social skills.

Overall, the contributions in the sample cover a notable variety of dependent and especially of independent variables associated with emotional responses. Yet, the reviewed research also seems to concentrate on a few constructs. Regarding the dependent variables, there is a strong focus on user acceptance, whereas for the independent variables, the main interest is in the human-like appearance and expression of AI agents as antecedents of emotional responses.

Finally, it is notable that emotional responses often figure not just as simply dependent or independent variables, but as mediating factors in the examined contributions. 52 of the 130 contributions in the sample examine the mediating effect of emotional constructs. Hence, there is a strong interest in including emotions in the analysis to probe specific mechanisms through which factors like anthropomorphism affect outcomes such as AI system use. This use of emotional responses as a mediating variable matters for the added value of including emotional responses, as we will discuss further below.

4.4 Key findings

Based on the preceding description, Figure 7 summarizes commonly studied relationships, listing the most common variables for each category as examples. We continue the analysis with a focus on key findings regarding the associations shown in the figure. We synthesize the main findings in the contributions, describing broader patterns concerning the role and relevance of emotional responses and highlighting findings that complement or contradict these broader patterns in important ways. We also examine to what extent the reviewed research has distinguished between an emotional and cognitive dimension or mechanism and what results follow from this distinction.

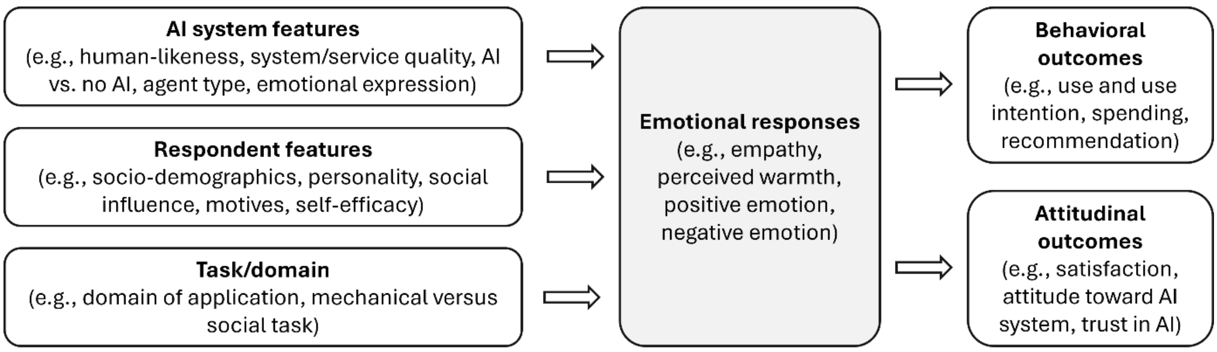

Figure 7: Overview of studied relationships

The first central finding emerging from the reviewed literature is that the emotional constructs with a positive valence – including generic emotional evaluations – are positively associated with a wide range of behavioral and attitudinal constructs. Contributions have repeatedly found that positive emotions lead to intended and actual use of AI systems, more positive perceptions of AI systems features like service quality, higher satisfaction, greater acceptance of AI and AI decisions, and more trust in AI. As one would expect, negative emotions consistently have opposite effects. Negative emotions lead to lower use intention, use, and spending behavior, more negative attitudes toward AI and toward the AI system provider, lower satisfaction, and lower trust.

The findings described so far generally concern AI-based services and the intention to use them. Some contributions deviate from this focus and examine the readiness to cooperate with AI agents. The three studies in the sample adopting this perspective find that the perceived warmth of an AI system increases people's likelihood of cooperating with an AI system. It is furthermore notable that several contributions studying the effects of emotional responses on attitudes toward the AI system *deployer* find significant positive associations (Ma, Dai, and Deng 2024; Pantano and Scarpi 2022; Pizzi et al. 2023). They thus indicate that there is a transfer in evaluations beyond the AI systems to those deploying them.

Only a few studies do not find an association between emotional constructs and behavioral and attitudinal outcomes (e.g., Acosta-Enriquez et al. 2024; Merrill, Kim, and Collins 2022). There is no systematic evidence on why these deviating non-findings emerge, but we highlight two possible explanations. First, some studies point to a need to nuance our understanding of the effects of concrete emotional responses. Different concrete emotions may have different effects. Anxiety (Hong and Cho 2023) and discomfort (Hsieh 2023), for instance, do not seem to lower intention to use. Second, the concrete setting might shape what role emotions play for people’s interactions with AI systems. One study finds a negative effect of positive emotional responses on purchase outcomes and points to the particularities of the setting as the reason for this finding (Elmashhara et al. 2024). Specifically, the authors argue that increasing the emotional engagement with gamified AI applications is already so rewarding for users that they are less likely to continue with purchases that these systems potentially promote.

A second strong theme emerging from the reviewed research is that among the predictors of emotional responses, agent characteristics are positively associated with positive emotional responses. AI systems' human-likeness and emotional or empathy impression, but also their interactivity, autonomy, the perceived social closeness of AI systems (including self-congruence and in-group membership), and signals of cooperativeness all are important predictors of positively connotated emotional constructs, particularly empathy and warmth. The type of agent and intelligence also seem to matter, but the results are not conclusive. While one study (Pantano and Scarpi 2022) found that non-social forms of intelligence such as logic-mathematical intelligence lead to more positive emotion, another study (Schepers et al. 2022) found that thinking and feeling, as opposed to mechanical AI and perceived autonomy, lead to more positive emotion. The effects of the gender of an AI system on emotional responses equally remain unclear.

Other AI system features that concern the quality of the system or the provided service are also significant predictors. Features like performance expectancy, perceived usefulness, ease of use, interaction convenience, and transparency lead to more positive emotional responses on balance. Weaker positive emotions or stronger negative emotions also regularly result from perceived risks and undesirable behaviors or outcomes of AI system, such as experienced discrimination, perceiving AI as defeating humans, AI committing errors.

Third, those studies that explicitly contrast the use of an AI system versus a human performing a task or providing a service present a largely consistent pattern regarding emotional responses. Using an AI system leads to more negative emotions, specifically lower perceived warmth and empathy and higher creepiness (but see Mancone et al. 2023; Brady et al. 2024). The sample also contains two studies that – at least partially – contradict each other on whether people react more intensely to AI systems than to humans when these systems make errors or contradict users. Leyer et al. (2019) observe that when individuals' decisions to delegate led to unfavorable outcomes, they were angrier after having delegated to a colleague than to an algorithm. Renier et al. (2021), in turn, report that compared to a human, an AI system committing an error leads to more negative emotional reactions.

Fourth, while emotional creepiness or eeriness is a less common emotional response than, e.g., joy and discomfort, its antecedents are similar to those of both general and concrete negative emotions. A high degree of human-likeness of AI agents leads to feelings of creepiness, as do perceived harm and injustice, and the mere use of AI can lead to creepiness in social settings, such as when AI is used in interviews. Furthermore, thought-detecting AI agents lead to higher eeriness than emotion-detecting agents. The perceived usefulness and transparency of an AI system, in turn, lower emotional creepiness. Besides AI system features, research has found various personal dispositions – privacy concerns, technology anxiety, and the need for human interaction – to be antecedents of higher creepiness. There is less evidence in the reviewed contributions on the consequences of creepiness, but it seems to engender less trust and continued use, like other emotions with negative valence.

Fifth, findings on the role of personal characteristics suggest that people can be pre-disposed in various ways toward having more positive or more negative emotions toward AI. Particularly, prior trust in an AI system is consistently with emotions of a positive valence. People's self-efficacy, technology familiarity and domain experience also seem to lead to more positive emotions, as does a hedonistic motivation. Besides motivation, personality appears to play an important role in individuals' evaluation of AI in emotional terms. Evidence in the reviewed research suggests that neuroticism, extraversion, agreeableness, low conscientiousness, low personal innovativeness, and a sense of uniqueness lead to more negative emotions. Further relevant antecedents of emotions toward AI systems with valence are social influence and individuals' prior attitudes, whereas and concrete concerns, such as about privacy, lead to less positive or more negative emotion.

Finally, although the role of the context has not been investigated extensively in the reviewed contributions, there is clear evidence that the setting of AI use, specifically the domain and the kinds of tasks, are important for people's emotional responses. Four of the five studies find that the domain of an AI application matters for emotional responses. A consistent finding tasks with a social or hedonic component are associated with more negative emotions toward AI systems.

Emotional responses are important determinants of behavioral and attitudinal outcomes and they have antecedents in various AI features and personal dispositions. They matter for how much people interact or intend to interact with AI systems and whether they hold positive attitudes toward them. Indeed, in the examined contributions, emotions frequently feature as powerful predictors of outcomes like use or intention to use or AI attitudes (e.g., Gao et al. 2024; Xu et al. 2024; Chi and Hoang Vu 2023). About a fifth of all examined contributions also explicitly distinguish between a cognitive and an emotional dimension or mechanism in how people relate to AI systems. These contributions highlight the importance of making this distinction and commonly point to a comparatively strong impact of emotional constructs in comparison with functional and cognitive evaluations (e.g., Renier, Schmid Mast, and Bekbergenova 2021; Lv et al. 2022; Xu et al. 2024; Sun, Hu, and Wu 2024). To properly understand how people perceive and interact with AI systems, it thus seems crucial to explicitly consider an emotional dimension.

4.5 Discussion of responsible AI use in the reviewed research

Given the manipulative potential of AI systems engendering emotional responses, a further important question is to what extent the reviewed contributions discuss the implications of their findings for responsible AI use. The share of studies discussing ethical and societal impacts of AI systems is low. Only 13 of the 130 reviewed contributions explicitly refer to these aspects. Several studies make general statements about the social implications and ethical consequences of the use of AI systems (e.g., Lee et al. 2024; M. Sun, Hu, and Wu 2024). Other articles point to concerns among respondents and to determinants of AI system use that have ethical relevance (e.g., Lee 2018; Grundke, Stein, and Appel 2022; Wu, Huang, and Li 2023). Only a few contributions discuss implications following from evidence about emotional responses to AI systems. Each study highlights specific ethical challenges. Yanit et al. (2023) point to the ethical risk that AI systems capable of emulating empathy are increasingly used for tasks that require authentic human empathy. They show that such uses lead to low acceptance as people perceive AI systems as inadequate for such tasks. Based on evidence about emotional responses to voice modulation of AI systems, Efthymiou and Hildbrand (2024) caution that a human-like voice can manipulate individuals, e.g., by triggering compassion through a trembling in the voice. Borau et al. (2021) caution that female gendering of AI increases the perceived humanness and warmth and that deployers could use this effect instrumentally while reinforcing harmful gender stereotypes and objectifying women. These contributions highlight important implications of studying emotional responses to AI systems. Overall, however, it is rare in the sample of reviewed contributions that they explicitly discuss how emotional responses to AI can mean challenges for ensuring responsible AI uses.

At the same time, many studies focus on the potential instrumental use of the emotional responses AI systems can engender, specifically by shaping people's – commonly customers' – behaviors and attitudes. For instance, one study recommends practitioners to "leverage […]

artificial empathy" when designing chatbots in the tourism sector to make customers more enthusiastic about interacting with AI agents (Fan, Han, and Wang 2023, 17–18). Similar recommendations are that "practitioners should consider introducing specific AI types based on consumers' emotions they want to generate" (Pantano and Scarpi 2022, 596) or that practitioners should not disclose chatbots' identities [i.e., that they are chatbots and not humans, the authors] to avoid negative emotional responses (Fan, Han, and Wang 2023; Tsumura and Yamada 2023). This utilitarian and instrumental view, which can easily justify unethical uses or render them seemingly unproblematic, is widespread in the reviewed research.

5. Discussion

5.1 The added value of including emotional responses to AI systems

Our review suggests that emotional responses play an important role in people's perceptions of and interactions with AI systems. There is a range of personal characteristics that lead people to feel positive or negative emotions regarding AI systems. Already the mere use of AI systems for a given task can often lead to less positive or more negative emotions. Most importantly, features of AI systems, and most notably characteristics that make them more agent- or person-like, can induce more positive emotional responses. These responses themselves lead to a range of behavioral and attitudinal outcomes. However, precisely because emotional responses are so commonly related to such a broad range of other constructs, an important question is where the added value of including emotions lies – as compared to simply looking at attitudes toward AI systems, such as the evaluation or perceived acceptability of AI system use.

The reviewed contributions point to several ways in which studying the role of emotional responses can be particularly insightful. First, in line with the stimulus-organism-response model, emotions can be an important mediator that channels the effect of various determinants such as the human-likeness of an AI system on final outcomes like AI system use or attitudes toward an AI system. Studying the mediating role of emotions can show to what extent emotional responses are more closely tied to certain determinants of, e.g., AI use than others (such as specific features of an AI system). Second, the relevance of emotions becomes particularly evident when comparing the effects of emotions to other, non-emotional constructs like the perceived performance of an AI system. At least some of the reviewed contributions indicate that emotional responses can engender behavioral and attitudinal outcomes separate from other influences, such as cognitive evaluations of functional aspects of an AI system. Highlighting such different mechanisms can be crucial for understanding how people form attitudes toward AI systems in less deliberate and conscious ways.

The described emotion-cognition distinction also has important consequences for the theoretical foundations used in the study of interactions with AI systems. The examined contributions often use behavioral and attitudinal dependent variables common in technology acceptance models (TAM) – particularly intended or actual use. Features concerning system quality and personal characteristics found in the technology acceptance model are also prominent in the reviewed research. Yet, as several contributions state, the TAM is not suitable for analyzing interactions with AI systems because it focuses on utilitarian, cognitive factors and does not adequately capture a social and emotional dimension of AI use (e.g., Ng, Hao, and Zhang 2024; Yin, Wang, and Liu 2024). To address this limitation, researchers either combine emotional constructs with TAM elements or they draw on alternative theoretical foundations, such as transactional theory (Yin, Wang, and Liu 2024).

AI systems are fundamentally different from previous technologies to the extent that they have an agent-like character. The exclusion of emotional responses from TAM research represents a significant shortcoming. TAM is grounded in the theory of planned behavior, which excludes emotional responses on the premise that they are often not deliberate or conscious processes. As emotions become increasingly significant in human-AI interactions, particularly as AI systems develop more agent-like characteristics, the TAM becomes increasingly inadequate through lacking emotional responses.

As our review demonstrates, emotional responses constitute important constructs in human-AI interactions. They not only mediate the effects of objective or perceived properties of AI systems on outcomes such as system use, but various studies in this review suggest that emotional constructs may actually be more important than cognitive, functional evaluations of AI systems. Furthermore, the review highlights various unique characteristics of AI agents that traditional technology acceptance models do not address. These AI-specific factors include human-likeness, perceived social group membership, and AI systems that emulate empathy or emotions, among others. For the TAM to adequately accommodate these particularities and the role of emotions, it should integrate frameworks in which emotional responses are more central. The stimulus-response model, for instance, incorporates emotional responses that mediate the impact of prior stimuli on outcomes, while the appraisal theory of emotions (Moors et al. 2013) explicitly conceptualizes emotions as an appraisal of the environment regarding its importance for someone's well-being.

Various conceptual foundations could potentially complement the TAM. However, in any case, it seems essential to account for emotional responses as factors that operate partly separate from more conscious and deliberate evaluations of AI systems. Such a more unconscious mechanism regulating people's interactions with AI systems is particularly relevant for understanding possible gaps between how much trust people place in AI systems and the trustworthiness of the systems, as studied in research dealing with appropriate trust (Mehrotra, Degachi, et al. 2024). Emotions can be important for regulating and calibrating people's trust in AI systems. They can contribute to people learning to trust AI systems that are safe, ethical, and reliable, but they may also induce trust where skepticism is warranted. What emotional responses AI systems engender will thus arguably be crucial for people developing a balanced relationship with this technology.

5.2 Future research avenues

The findings from our review also point to several possible directions for future research. First, a notable gap in the reviewed research is that contributions rarely investigate concrete emotions, such as anger, fear and joy, although they are sometimes used and combined into composite measures like positive or negative emotion. Yet, studying different concrete emotions could show how AI systems and their features may lead to certain emotional responses but not others, and how different emotions could have different outcomes. The theory of affective intelligence suggests that concrete emotions have different consequences for opinion formation and behavior (Marcus and Mackuen 1993). This expectation may also hold true for AI systems. Overall, there is a need to gain a more nuanced picture of emotional responses to AI systems and how these matter for various outcomes.

Second, the reviewed contributions have rarely examined the relation between emotions and trust in AI. Only few reviewed contributions include trust as an outcome, which is striking when considering how central trust features in debates about AI perceptions (see, e.g., Glikson and Woolley 2020) and in policy debates about trustworthy AI (Laux, Wachter, and Mittelstadt 2024). It is also notable that trust features both as an outcome and a predictor of emotional responses. While both relationships can make sense, the choice of perspective matters for the kind of mechanisms that we presume and for the ways in which emotional responses become relevant. For instance, one of the reviewed studies found that trust in an AI system is evoked via emotional responses rather than cognitive evaluations of AI systems (Sun, Hu, and Wu 2024). If this finding is corroborated, it suggests that studying emotional responses as a predictor of trust is valuable for understanding mechanisms underlying trust formation.

At the same time, a close relationship between trust and emotions may be inherent to the concept of trust itself. The influential definition of trust by Mayer (1995) specifies perceived ability, benevolence, and integrity as core dimensions of trust. There is a conceptual overlap between benevolence and warmth – conveying friendliness and caring – that raises concerns about a potential conflation of these constructs. An overlap between emotions and trust is also visible in the distinction between cognitive and emotional trust (Zheng et al. 2023) and in the idea that the formation of trust involves users developing a emotional bond over time through continued engagement (Mehrotra, Jorge, et al. 2024). These considerations underscore the importance of disentangling trust from emotional constructs and systematically analyzing relationships between them.

A third possible direction for future research is to depart from the common methodological approach in the reviewed contributions. A majority of the examined contributions uses convenience samples, many of which are of rather limited size (a median of 322 respondents per study, see Appendix A8 for details). Larger samples and especially quota or random samples would contribute to the generalizability of the findings. Furthermore, the dominant approach to studying emotional responses and evaluations is experimental designs. These are suitable for testing reactions to AI systems. Yet, there is a lack of public opinion studies that can claim to be representative of the population of one or more countries. Such studies could also examine relationships that, although they are not based on experimental designs, can shed light on the personal dispositions which lie behind different emotional evaluations of AI.

5.2 Implications for responsible AI use and for AI governance

Overall, the reviewed research on emotional responses to AI shows a predominant concern with making AI systems acceptable to people. Many of the reviewed contributions point to how AI systems can evoke emotional responses that lead to desired outcomes, such as use and satisfaction. They discuss how AI systems can trigger emotional reactions and social perceptions that foster acceptance of these systems – including ways to compensate for functional deficits of AI systems. There is thus a largely instrumental view on emotional constructs, which also manifests in the focus on use and satisfaction as dependent variables.

Furthermore, the most frequently investigated antecedents of emotional responses are variables that are particularly relevant for emulating humans and human interaction, particularly human-likeness and emotional expressions. However, as such emotional expressions are necessarily inauthentic, they raise ethical questions. On the one hand, emulating and evoking emotions can make interactions with AI systems more pleasant. On the other hand, they can be deceptive and manipulative. AI systems may be designed to treat individuals merely as objects whose behaviors are to be shaped by evoking emotions to realize certain goals, like AI system uptake. A few studies even suggest not disclosing the interaction with an AI system.

5.4 Limitations

While this systematic review provides a comprehensive mapping of research on emotional responses to AI systems, it is not without limitations. First, the review focused on research using standardized surveys for the sake of broad coverage while ensuring comparability. We have also limited the selection to contributions with at least 100 participants. Yet, there exists research using different methods like neuro-imaging, focus groups or qualitative interviews that can also shed light on emotional responses to AI systems. Quantitative studies from human-computer interaction studies with less than 100 participants – despite this being a low number for survey research – may hold further relevant insights. Future research could extend the review above and systematically look at other approaches and how findings from this research compares to those presented above. Second, as the review broadly covered emotional responses to AI systems, specific aspects, such as differences in the measurement of individual constructs like empathy or creepiness, could not be examined in depth. Future research can take this review as a starting point and delve further into aspects that could only be touched upon in the analysis above. This could mean looking more closely at specific emotional constructs or the role of moderating variables. Finally, as shown further above, the reviewed field of research is growing very quickly. The state of research may show notable shifts in the coming years. It will thus be instructive to undertake another stocktaking and examine how the field develops at a later time.

6. Conclusion

We set out to take stock of what is known about emotional responses to AI systems. Our review has shown that research on emotional responses to AI systems shows a strong focus on systems interacting with individuals as customers, specifically in marketing, retail, and e-commerce, and in finance and tourism. While health is also a frequent domain, public sector uses, such as in education or government are less frequent. The review furthermore documents that emotional responses are key factors causing behavioral and attitudinal outcomes, especially intention to use an application and user satisfaction. Among the antecedents of emotional responses, AI systems features that make these systems more agent- and human-like have been studied the most. They are also important causes of emotional responses to AI agents. Finally, we identified a predominant interest in the instrumental value of emotions for engendering desired behaviors and evaluations. Despite a clear potential of designing AI systems to subconsciously influence and manipulate users through emotions, there is overall little reflection on what findings about emotional responses imply for responsible AI use.

The results of our review are especially timely as policymakers worldwide work on governance structures that account for AI's expanding capabilities and their societal impacts. Future governance frameworks should incorporate insights into emotional responses to AI systems to ensure that as these systems evolve from functional tools to social agents, they do so in ways that respect emotional well-being and human agency. The review offers important insights in this regard and can inform efforts to ensure responsible AI uses and draft suitable governance frameworks. The compiled evidence indicates that as AI agents increasingly simulate human-like emotional interactions, thereby creating unprecedented regulatory challenges around manipulation, trust exploitation, and psychological harm. Without appropriate governance guardrails, AI systems may leverage emotional responses to influence user behavior in ways that might undermine personal autonomy or exploit psychological vulnerabilities—whether in commercial, healthcare, or educational contexts. In view of these challenges, Ciriello et al. (2025) have argued for a "compassionate AI design" which ensure that people are treated as ends and not as mere means, and that prioritizes dignity, authentic empathy, and human flourishing.

Existing AI governance does not yet sufficiently address the crucial role of the emotional dimension in human-AI interaction. Ensuring responsible AI use requires rules that prevent practices which are deceptive or manipulative. The comprehensive AI regulation by the European Union, the AI Act, requires providers of AI systems to disclose when a person is interacting with an AI system (Article 50). It also prohibits certain uses, including AI systems that are "purposefully manipulative or deceptive techniques" and applications that infer people's emotions (Article 5). However, the reviewed research also points to various uses that are not outright deceptive or manipulative, but that may still be hard to reconcile with respecting the autonomy of individuals interacting with AI systems.

Our review thus points to crucial aspects that can inform the development of balanced regulatory approaches which mitigate risks of emotional manipulation while preserving beneficial AI-human emotional engagement. The findings above suggest that such a balanced regulatory approach would address risks for human autonomy that come with making AI systems more agent- and human-like, including through emulating empathy and emotional expressions – which is commonly justified with enhanced user experience. To preserve human autonomy and dignity, AI development and use need to be directed toward making AI systems convenient without however triggering certain emotions that come from inauthentic human-like characteristics of these systems. Impact assessments an certification schemes for AI systems could also explicitly incorporate the emotional dimension to avoid manipulative uses and make users aware of what kind of agent they are interacting with. Governance for trustworthy AI may also require devising some kind of emotional etiquette for AI agents regarding their human-likeness and emotional expressions.

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Appendix

Contents

Appendix A1: Search string used for the preliminary search

To identify additional relevant keywords intended to cover constructs measuring emotional responses to AI systems, we first conducted a preliminary search with only “emotion*”, “sentiment*”, and “feeling*“ as keywords capturing emotional constructs. For this preliminary search in Scopus we used the otherwise identical search string as for the main search (see Appendix A2 below), but chose only psychological journals because psychology traditionally studies emotions and because this yields a feasible number of contributions used in a preliminary search. This preliminary search yielded 416 hits, whose titles and abstracts have been screened for additional relevant search terms. Through this preliminary search, we obtained “empathy”, “warmth”, “mood” as further relevant keywords. Using these additional keywords for the full search described below changes the overall number of entries for the complete search (Appendix A2) from 5,211 to 5,791.

The search string for the preliminary search in Scopus is as follows:

> TITLE-ABS-KEY (("artificial intelligence" OR algorithm*) AND (emotion* OR “sentiment*” OR “feeling*“) AND (experiment* OR survey* OR *study OR *studies) AND (participants OR respondents OR subjects OR reaction* OR response* OR attitude* OR perception*)) AND PUBYEAR > 2014 AND PUBYEAR < 2025 AND (LIMIT-TO (SUBJAREA , "PSYC")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (SRCTYPE , "p") OR LIMIT-TO (SRCTYPE , "j"))

Appendix A2: Full search string for the main search

The search string for the search in Scopus is as follows:

> TITLE-ABS-KEY (("artificial intelligence" OR algorithm*) AND (emotion* OR “sentiment*” OR “feeling*“ OR mood OR empathy OR warmth) AND (experiment* OR survey* OR *study OR *studies) AND (participants OR respondents OR subjects OR reaction* OR response* OR attitude* OR perception*)) AND PUBYEAR > 2014 AND PUBYEAR < 2025 AND (LIMIT-TO (SUBJAREA , "COMP") OR LIMIT-TO (SUBJAREA , "ENGI") OR LIMIT-TO (SUBJAREA , "MEDI") OR LIMIT-TO (SUBJAREA , "SOCI") OR LIMIT-TO (SUBJAREA , "NEUR") OR LIMIT-TO (SUBJAREA , "DECI") OR LIMIT-TO (SUBJAREA , "PSYC") OR LIMIT-TO (SUBJAREA , "MULT") OR LIMIT-TO (SUBJAREA , "HEAL") OR LIMIT-TO (SUBJAREA , "ECON") OR LIMIT-TO (SUBJAREA , "NURS")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (SRCTYPE , "p") OR LIMIT-TO (SRCTYPE , "j"))

Appendix A3: Inclusion criteria

The screening of the full texts of the contributions for their inclusion meant applying the following criteria in the order as described. Sources were excluded based on substantive criteria that concern what the contributions study. We excluded entries if they are not about emotional responses to AI. For instance, an abstract may mention a survey that contains questions about feelings regarding AI, but a study then measures general attitudes toward AI and not emotions. We also excluded contributions that turned out to study emotional responses to the mere content generated with AI rather than to AI systems. The methodological exclusion criteria refer to aspects concerning the research design of the screened contributions. We excluded studies that did not contain an empirical analysis (e.g., theoretical articles), did not use a survey (e.g., analyzed social media content), did use a survey but no standardized items to measure emotional constructs (e.g., qualitative interview studies), did not describe the measurement items in a way that is reproducible, or had overall observation numbers lower than 100. For survey research using standardized questionnaires, at least a couple of hundred cases are commonly desirable for a certain degree of reliability and generalizability. We therefore regard 100 respondents as a low minimum threshold. Besides these substantive and methodological criteria, which are listed below, a dozen of contributions was also excluded because they could not be retrieved.

List of inclusion criteria:

- Studies emotional responses (emotional reactions to AI systems or evaluations of AI that have an emotional dimension, such as perceived emotional intelligence).
- Studies emotional responses to *AI systems* and not just to content produced by AI systems (such as artwork).
- Conducts an empirical analysis.
- Conducts a survey.
- Uses a standardized survey with closed questions.
- The items for examined emotional constructs are reproducible
- The sample size is at least 100 respondents.

Appendix A4: List of included contributions

Authors	Date	Title
Acosta-Enriquez B.G.; Arbulú Ballesteros M.A.; Huamaní Jordan O.; López Roca C.; Saavedra Tirado K.	2024	Analysis of college students' attitudes toward the use of ChatGPT in their academic activities: effect of intent to use, verification of information and responsible use
Almufarreh A.	2024	Determinants of Students' Satisfaction with AI Tools in Education: A PLS-SEM-ANN Approach
Aw K.L.; Suepiantham S.; Rodriguez A.; Bruce A.; Borooah S.; Cackett P.	2023	Patients' Perception of Robot-Driven Technology in the Management of Retinal Diseases
Behn O.; Leyer M.; Iren D.	2024	Employees' acceptance of AI-based emotion analytics from speech on a group level in virtual meetings
Belanche D.; Casaló L.V.; Schepers J.; Flavián C.	2021	Examining the effects of robots' physical appearance, warmth, and competence in frontline services: The Humanness-Value-Loyalty model
Bera A.; Randhavane T.; Kubin E.; Wang A.; Gray K.; Manocha D.	2018	The Socially Invisible Robot Navigation in the Social World Using Robot Entitativity
Binesh F.; Baloglu S.	2023	Motivational, Situational, and Psychological Model of Service Robot Adoption in Hotels: The Moderating Role of Involvement
Bochniarz K.T.; Czerwiński S.K.; Sawicki A.; Atroszko P.A.	2022	Attitudes to AI among high school students: Understanding distrust towards humans will not help us understand distrust towards AI
Borau S.; Otterbring T.; Laporte S.; Fosso Wamba S.	2021	The most human bot: Female gendering increases humanness perceptions of bots and acceptance of AI
Brady A.C.; Botnaru D.; Alt K.; Carroll G.D.; Moldavan A.M.; Mesenbrink-Sainz J.; Nafziger B.; Reagan K.J.; Rich L.E.	2024	Understanding the Influence of Intelligent Agents on Students' Sense of Classroom Belonging, Engagement, and Academic Performance in Online Classes
Cai Z.; He H.; Huo W.; Xu X.	2023	More Unique, More Accepting? Integrating Sense of Uniqueness, Perceived Knowledge, and Perceived Empathy with Acceptance of Medical Artificial Intelligence
Chen L.; Sun R.; Yuan Y.; Zhan X.	2024	The influence of recommendation algorithm's information flow on targeted advertising audience's coping behavior
Chen Q.; Yin C.; Gong Y.	2023	Would an AI chatbot persuade you: an empirical answer from the elaboration likelihood model
Cheng X.; Bao Y.; Zarifis A.; Gong W.; Mou J.	2022	Exploring consumers' response to text-based chatbots in e-commerce: the moderating role of task complexity and chatbot disclosure
Chi N.T.K.; Hoang Vu N.	2023	Investigating the customer trust in artificial intelligence: The role of anthropomorphism, empathy response, and interaction
Chi O.H.; Gursoy D.; Chi C.G.	2022	Tourists' Attitudes toward the Use of Artificially Intelligent (AI) Devices in Tourism Service Delivery: Moderating Role of Service Value Seeking
Choi S.; Lee C.-J.; Park A.; Lee J.A.	2024	How the Public Makes Sense of Artificial Intelligence: The Interplay Between Communication and Discrete Emotions
De Melo C.M.; Gratch J.; Carnevale P.J.	2015	Humans versus computers: Impact of emotion expressions on people's decision making
Derinalp P.; Ozyurt M.	2024	Adaptation of the Student Attitudes Toward Artificial Intelligence Scale to the Turkish Context: Validity and Reliability Study
Dhavraj K.; Ndoro T.T.R.	2023	The Drivers of Customer Satisfaction in Interactions with Virtual Agents: Evidence from South Africa
Downen T.; Kim S.; Lee L.	2024	Algorithm aversion, emotions, and investor reaction: Does disclosing the use of AI influence investment decisions?
Efthymiou F.; Hildebrand C.	2024	Empathy by Design: The Influence of Trembling AI Voices on Prosocial Behavior
Elmashhara M.G.; De Cicco R.; Silva S.C.; Hammerschmidt M.; Silva M.L.	2024	How gamifying AI shapes customer motivation, engagement, and purchase behavior
Elor A.; Kurniawan S.; Takayama L.	2022	Human Experiences in Teaching Robots: Understanding Agent Expressivity and Learning Effects through a Virtual Robot Arm
Fan H.; Han B.; Wang W.	2023	Aligning (In)Congruent Chatbot–Employee Empathic Responses with Service-Recovery Contexts for Customer Retention
Faruk L.I.D.; Pal D.; Funilkul S.; Perumal T.; Mongkolnam P.	2024	Introducing CASUX: A Standardized Scale for Measuring the User Experience of Artificial Intelligence Based Conversational Agents
Frank D.-A.; Otterbring T.	2023	Being seen… by human or machine? Acknowledgment effects on customer responses differ between human and robotic service workers
Gao J.; Wang H.; Li W.; Li G.; He S.	2024	Research on the Effect of the Empathy Ability of AI Service Robots on Consumer Well-Being: The Chain Mediating Model
Gao L.; López-Pérez M.E.; Melero-Polo I.; Trifu A.	2024	Ask ChatGPT first! Transforming learning experiences in the age of artificial intelligence
Grundke A.; Stein J.-P.; Appel M.	2022	Mind-Reading Machines: Distinct User Responses to Thought-Detecting and Emotion-Detecting Robots
Gupta V.	2024	An Empirical Evaluation of a Generative Artificial Intelligence Technology Adoption Model from Entrepreneurs' Perspectives
Han E.; Yin D.; Zhang H.	2023	Bots with Feelings: Should AI Agents Express Positive Emotion in Customer Service?
Harris-Watson A.M.; Larson L.E.; Lauharatanahirun N.; DeChurch L.A.; Contractor N.S.	2023	Social perception in Human-AI teams: Warmth and competence predict receptivity to AI teammates

Haupt M.; Rozumowski A.; Freidank J.; Haas A.	2023	Seeking empathy or suggesting a solution? Effects of chatbot messages on service failure recovery
Hong J.-W.; Choi S.; Williams D.	2020	Sexist AI: An Experiment Integrating CASA and ELM
Hong S.J.; Cho H.	2023	The role of uncertainty and affect in decision-making on the adoption of AI-based contact-tracing technology during the COVID-19 pandemic
Hsieh P.-J.	2023	Determinants of physicians' intention to use AI-assisted diagnosis: An integrated readiness perspective
Hu M.; Zhang G.; Chong L.; Cagan J.; Goucher-Lambert K.	2024	How Being Outvoted by AI Teammates Impacts Human-AI Collaboration
Hu Q.; Lu Y.; Pan Z.; Gong Y.; Yang Z.	2021	Can AI artifacts influence human cognition? The effects of artificial autonomy in intelligent personal assistants
Hu Y.; Xiao Y.; Hua Y.; Fan Y.; Li F.	2024	The More Realism, the Better? How Does the Realism of AI Customer Service Agents Influence Customer Satisfaction and Repeat Purchase Intention in Service Recovery
Huang S.Y.B.; Lee C.-J.; Lee S.-C.	2021	Toward a unified theory of customer continuance model for financial technology chatbots
Huang T.	2022	What Affects the Acceptance and Use of Hotel Service Robots by Elderly Customers?
Hui Z.; Khan A.N.; Chenglong Z.; Khan N.A.	2023	When Service Quality is Enhanced by Human–Artificial Intelligence Interaction: An Examination of Anthropomorphism, Responsiveness from the Perspectives of Employees and Customers
Jin G.; Jiang J.; Liao H.	2024	The work affective well-being under the impact of AI
Kang J.-Y.M.; Choi D.	2023	Artificial intelligence-powered digital solutions in the fashion industry: a mixed-methods study on AI-based customer services
Katsantonis A.; Katsantonis I.G.	2024	University Students' Attitudes toward Artificial Intelligence: An Exploratory Study of the Cognitive, Emotional, and Behavioural Dimensions of AI Attitudes
Kavitha K.; Joshith V.P.; Sharma S.	2024	Beyond text: ChatGPT as an emotional resilience support tool for Gen Z – A sequential explanatory design exploration
Khadpe P.; Krishna R.; Fei-Fei L.; Hancock J.T.; Bernstein M.S.	2020	Conceptual Metaphors Impact Perceptions of Human-AI Collaboration
Kim A.; Cho M.; Ahn J.; Sung Y.	2019	Effects of Gender and Relationship Type on the Response to Artificial Intelligence
Kim J.; Im I.	2023	Anthropomorphic response: Understanding interactions between humans and artificial intelligence agents
Kim S.; Jung Y.	2023	Development of Semantic Differential Scales for Artificial Intelligence Agents
Kim S.; Lee J.; Oh P.	2024	Questioning Artificial Intelligence: How Racial Identity Shapes the Perceptions of Algorithmic Bias
Kim S.; Oh P.; Lee J.	2024	Algorithmic gender bias: investigating perceptions of discrimination in automated decision-making
Kim T.W.; Lee H.; Kim M.Y.; Kim S.A.; Duhachek A.	2023	AI increases unethical consumer behavior due to reduced anticipatory guilt
Klein U.; Depping J.; Wohlfahrt L.; Fassbender P.	2023	Application of artificial intelligence: risk perception and trust in the work context with different impact levels and task types
Lee C.T.; Pan L.-Y.; Hsieh S.H.	2022	Artificial intelligent chatbots as brand promoters: a two-stage structural equation modeling-artificial neural network approach
Lee M.K.	2018	Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management
Lee S.; Jones-Jang S.M.; Chung M.; Kim N.; Choi J.	2024	Who is using ChatGPT and why?: Extending the Unified Theory of Acceptance and Use of Technology (UTAUT) model
Lee S.; Park G.; Chung J.	2023	Artificial emotions for charity collection: A serial mediation through perceived anthropomorphism and social presence
Leyer M.; Schneider S.	2019	Me, you or ai? How do we feel about delegation
Li B.; Yao R.; Nan Y.	2024	How does anthropomorphism promote consumer responses to social chatbots: mind perception perspective
Li H.	2023	Rethinking human excellence in the AI age: The relationship between intellectual humility and attitudes toward ChatGPT
Li S.; Mou Y.; Xu J.	2024	Disclosing Personal Health Information to Emotional Human Doctors or Unemotional AI Doctors? Experimental Evidence Based on Privacy Calculus Theory
Liao S.; Lin L.; Pei H.; Chen Q.	2024	How does the status of errant robot affect our desire for contact?–The moderating effect of team interdependence
Liao X.; Zheng Y.-H.; Shi G.; Bu H.	2024	Automated social presence in artificial-intelligence services: Conceptualization, scale development, and validation
Lin H.; Chen Q.	2024	Artificial intelligence (AI) -integrated educational applications and college students' creativity and academic emotions: students and teachers' perceptions and attitudes
Lin R.-R.; Lee J.-C.	2022	The supports provided by artificial intelligence to continuous usage intention of mobile banking: evidence from China
Liu G.L.; Darvin R.; Ma C.	2024	Unpacking the role of motivation and enjoyment in AI-mediated informal digital learning of English (AI-IDLE): A mixed-method investigation in the Chinese context
Lu H.	2024	Exploring the predictors of public acceptance of artificial intelligence-based resurrection technologies
Lulu-Pokubo E.P.; Okwu E.	2024	Librarians' awareness towards the use of artificial intelligence technologies for Sustainable library services
Lv X.; Yang Y.; Qin D.; Cao X.; Xu H.	2022	Artificial intelligence service recovery: The role of empathic response in hospitality customers' continuous usage intention

Ma Y.M.; Dai X.; Deng Z.	2023	Using machine learning to investigate consumers' emotions: the spillover effect of AI defeating people on consumers' attitudes toward AI companies
Mancone S.; Diotaiuti P.; Valente G.; Corrado S.; Bellizzi F.; Vilarino G.T.; Andrade A.	2023	The Use of Voice Assistant for Psychological Assessment Elicits Empathy and Engagement While Maintaining Good Psychometric Properties
Martini M.C.; Gonzalez C.A.; Wiese E.	2016	Seeing minds in others - Can agents with robotic appearance have human-like preferences?
Mazid I.; Wallace A.; Chen J.; Choi S.	2024	Exploring Key Drivers for Embracing Artificial Intelligence in Public Relations Pedagogy
McKee K.R.; Bai X.; Fiske S.T.	2023	Humans perceive warmth and competence in artificial intelligence
McKee K.R.; Bai X.; Fiske S.T.	2024	Warmth and Competence in Human-Agent Cooperation
Mei H.; Bodog S.-A.; Badulescu D.	2024	Artificial Intelligence Adoption in Sustainable Banking Services: The Critical Role of Technological Literacy
Merrill K., Jr.; Kim J.; Collins C.	2022	AI companions for lonely individuals and the role of social presence
Nader K.; Toprac P.; Scott S.; Baker S.	2024	Public understanding of artificial intelligence through entertainment media
Ng W.; Hao F.; Zhang C.	2024	From Function to Relation: Exploring the Dual Influences of Warmth and Competence on Generative Artificial Intelligence Services in the Hospitality Industry
Oostrom J.K.; Holtrop D.; Koutsoumpis A.; van Breda W.; Ghassemi S.; de Vries R.E.	2024	Applicant reactions to algorithm- versus recruiter-based evaluations of an asynchronous video interview and a personality inventory
Pal D.; Babakerkhell M.D.; Papasratorn B.; Funilkul S.	2023	Intelligent Attributes of Voice Assistants and User's Love for AI: A SEM-Based Study
Pantano E.; Scarpi D.	2022	I, Robot, You, Consumer: Measuring Artificial Intelligence Types and their Effect on Consumers Emotions in Service
Park J.; Woo S.E.	2022	Who Likes Artificial Intelligence? Personality Predictors of Attitudes toward Artificial Intelligence
Pelau C.; Dabija D.-C.; Ene I.	2021	What makes an AI device human-like? The role of interaction quality, empathy and perceived psychological anthropomorphic characteristics in the acceptance of artificial intelligence in the service industry
Pizzi G.; Vannucci V.; Mazzoli V.; Donvito R.	2023	I, chatbot! the impact of anthropomorphism and gaze direction on willingness to disclose personal information and behavioral intentions
Qin H.; Zhu Y.; Jiang Y.; Luo S.; Huang C.	2024	Examining the impact of personalization and carefulness in AI-generated health advice: Trust, adoption, and insights in online healthcare consultations experiments
Rajaobelina L.; Prom Tep S.; Arcand M.; Ricard L.	2021	Creepiness: Its antecedents and impact on loyalty when interacting with a chatbot
Rawool V.; Foroudi P.; Palazzo M.	2024	AI-powered voice assistants: developing a framework for building consumer trust and fostering brand loyalty
Renier L.A.; Schmid Mast M.; Bekbergenova A.	2021	To err is human, not algorithmic – Robust reactions to erring algorithms
Renz S.; Kalimeris J.; Hofreiter S.; Spörrle M.	2024	Me, myself and AI: How gender, personality and emotions determine willingness to use Strong AI for self-improvement
Ribeiro M.A.; Gursoy D.; Chi O.H.	2022	Customer Acceptance of Autonomous Vehicles in Travel and Tourism
Rolison J.J.; Gooding P.L.T.; Russo R.; Buchanan K.E.	2024	Who should decide how limited healthcare resources are prioritized? Autonomous technology as a compelling alternative to humans
Schepers J.; Belanche D.; Casaló L.V.; Flavián C.	2022	How Smart Should a Service Robot Be?
Shao R.	2023	An Empathetic AI for Mental Health Intervention: Conceptualizing and Examining Artificial Empathy
Sullivan Y.; de Bourmont M.; Dunaway M.	2022	Appraisals of harms and injustice trigger an eerie feeling that decreases trust in artificial intelligence systems
Sun M.; Hu W.; Wu Y.	2024	Public Perceptions and Attitudes Towards the Application of Artificial Intelligence in Journalism: From a China-based Survey
Sun Y.; Xu C.; Xu H.	2024	Social identity in trusting artificial intelligence agents: Evidence from lab and online experiments
Tong S.T.; Sopory P.	2019	Does integral affect influence intentions to use artificial intelligence for skin cancer screening? A test of the affect heuristic
Tsumura T.; Yamada S.	2023	Influence of agent's self-disclosure on human empathy
Vuong Q.-H.; La V.-P.; Nguyen M.-H.; Jin R.; La M.-K.; Le T.-T.	2023	AI’s Humanoid Appearance Can Affect Human Perceptions of Its Emotional Capability: Evidence from Self-Reported Data in the U.S
Wang C.; Li X.; Liang Z.; Sheng Y.; Zhao Q.; Chen S.	2024	The Roles of Social Perception and AI Anxiety in Individuals’ Attitudes Toward ChatGPT in Education
Wang L.; Li W.	2024	The Impact of AI Usage on University Students’ Willingness for Autonomous Learning
Watamura E.; Ioku T.; Mukai T.; Yamamoto M.	2023	Empathetic Robot Judge, we Trust You
Wen F.; Li Y.; Zhou Y.; An X.; Zou Q.	2024	A Study on the Relationship between AI Anxiety and AI Behavioral Intention of Secondary School Students Learning English as a Foreign Language
Wu L.; Chen Z.F.; Tao W.	2024	Instilling warmth in artificial intelligence? Examining publics’ responses to AI-applied corporate ability and corporate social responsibility practices
Wu P.F.; Summers C.; Panesar A.; Kaura A.; Zhang L.	2024	AI Hesitancy and Acceptability—Perceptions of AI Chatbots for Chronic Health Management and Long COVID Support: Survey Study

Wu W.; Huang X.; Li X.	2023	Technology moral sense: Development, reliability, and validity of the TMS scale in Chinese version
Xu J.; Ren X.; Huang Y.; Wu R.; Pan Y.	2024	Persist or Abandon? Exploring Chinese Users' Continuance Intentions Toward AI Painting Tools
Xu X.; Liu J.	2022	Artificial intelligence humor in service recovery
Xu Y.; Bradford N.; Garg R.	2023	Transparency Enhances Positive Perceptions of Social Artificial Intelligence
Xue J.; Niu Y.; Liang X.; Yin S.	2023	Unraveling the Effects of Voice Assistant Interactions on Digital Engagement: The Moderating Role of Adult Playfulness
Yang Y.; Tavares J.; Oliveira T.	2024	A New Research Model for Artificial Intelligence–Based Well-Being Chatbot Engagement: Survey Study
Yanit M.; Yanit M.; Wan F.	2023	Right agent, wrong level of hedonism: How high (vs low) hedonic values in AI-performed tasks lead to decreased perceptions of humanlikeness, warmth, and less consumer support
Yigit D.; Acikgoz A.	2024	Evaluation of future nurses' knowledge, attitudes and anxiety levels about artificial intelligence applications
Yin H.; Wang C.; Liu Z.	2024	Unleashing pre-service language teachers' productivity with generative AI: Emotions, appraisal and coping strategies
Yoganathan V.; Osburg V.-S.	2024	Heterogenous evaluations of autonomous vehicle services: An extended theoretical framework and empirical evidence
Yoo S.-R.; Kim S.-H.; Jeon H.-M.	2022	How Does Experiential Value toward Robot Barista Service Affect Emotions, Storytelling, and Behavioral Intention in the Context of COVID-19?
Yoon N.; Lee H.-K.	2021	Ai recommendation service acceptance: assessing the effects of perceived empathy and need for cognition
Yu C.; Cai N.; Yan J.; Zhou Y.	2024	Consumers' Tolerance When Confronted with Different Service Types in Service Retailing
Yu L.; Li Y.	2022	Artificial Intelligence Decision-Making Transparency and Employees' Trust: The Parallel Multiple Mediating Effect of Effectiveness and Discomfort
Yun J.; Park J.	2022	The Effects of Chatbot Service Recovery With Emotion Words on Customer Satisfaction, Repurchase Intention, and Positive Word-Of-Mouth
Yun J.H.; Lee E.-J.; Kim D.H.	2021	Behavioral and neural evidence on consumer responses to human doctors and medical artificial intelligence
Zhang X.; Shi Y.; Li T.; Guan Y.; Cui X.	2024	How Do Virtual AI Streamers Influence Viewers' Livestream Shopping Behavior? The Effects of Persuasive Factors and the Mediating Role of Arousal
Zhang Y.; Tan W.; Lee E.-J.	2024	Consumers' responses to personalized service from medical artificial intelligence and human doctors
Zhang Y.; Zhu J.; Chen H.; Jiang Y.	2024	Enhancing Trust and Empathy in Marketing: Strategic AI and Human Influencer Selection for Optimized Content Persuasion
Zhao Y.; Chen Y.; Sun Y.; Shen X.-L.	2024	Understanding users' voice assistant exploration intention: unraveling the differential mechanisms of the multiple dimensions of perceived intelligence
Zheng X.; Wang Y.-C.; Wei W.; Zhang L.; Huo D.	2023	The impact of service robots on consumer response: Examining the roles of consumers' service expertise and technology expertise
Zhuang K.	2024	A study of anthropomorphic behavior of intelligent service robots on user satisfaction

Appendix A5: Codebook

I General information

v01 Authors

Names of the authors of a contribution.

v02 Title

Title of the contribution.

v03 Date

Date of publication (as provided by Scopus at the time of the concluded search).

v04 Summary (text)

Text field containing a brief description of the aims of the study.

II Domains and applications

v05 Domains

The area in which the AI systems studied in a contribution are deployed.

Multiple mentions are possible.

- **Education:** Applications used in the education sector or for educational purposes, such as giving advice to students.
- **Finance:** Applications that are used in financial services, investment, and banking.
- **Health:** Applications used in the health care sector, e.g., to provide recommendations to medical practitioners.
- **Hospitality and tourism:** Applications in the hospitality and tourism sector, used, e.g., in hotels or restaurants.
- **Journalism:** Applications used to support or perform task in the journalism profession.
- **Marketing, e-commerce, retail:** Applications targeting or interacting with consumers in the context of shopping or advertising.
- **Mobility:** Applications used in the context of transportation, such as in self-driving vehicles.
- **Work:** Applications used in the work context, e.g., to make decisions about employees, support employees in performing certain work tasks, or supporting managers in decision-making.

- **Generic:** Applications for which no domain is specified, referring to AI use in general.
- **Other:** More specific and niche applications that do not fall under the categories above, such as AI systems used by charities and resurrection technology**.**

v06 AI systems

The kinds of AI systems examined in a contribution.

Multiple mentions are possible.

- **AI in general / unspecified**. No concrete form of AI system is mentioned. The analysis refers to AI in general or leaves it unspecified.
- **Emotion analytics:** AI systems that serve to analyze the emotions of individuals.
- **Recommender system.** AI systems that produce recommendations for their users.
- **Robots and automated vehicles:** Embodied AI systems, such as service robots and self-driving vehicles.
- **Scoring and decisions systems.** AI systems designed to generate scores or decisions about individuals that are themselves not the users of the AI systems. E.g., assessing the interview performance of job applicants.
- **Strong AI:** AI systems with capabilities that fall under general artificial intelligence systems (hypothetical).
- **Surveillance applications:** AI systems used for the surveillance of individuals.
- **Virtual agent:** AI systems that operate like an agent and that can have variable autonomy. Comprises, e.g., chatbots, text-based generative AI systems, simulated agents.

III Emotional responses

v07 Emotional constructs

The kinds of emotional responses studied in the contributions.

Multiple mentions are possible.

- **Achievement emotion:** Measures of a pleasant state with high certainty in achieving a goal and little effort required.
- **Anger:** Emotional constructs that measure anger.
- **Arousal:** Emotional constructs that measure arousal, i.e., the intensity of emotion.
- **Attentiveness:** Measures of an emotional response involving the desire to attend to a stimulus.
- **Challenge emotion:** Measures of an emotional response involving a motivation to seize an opportunity and pursue potential benefits.
- **Comfort:** Refers to measures of comfort.
- **Deterrence emotion:** Measures of an emotional experience of threat with a certain degree of control over the consequences.

- **Discomfort:** Comprises measures of discomfort, uneasiness, unnerving, and technical frustration.
- **Dominance:** Emotional constructs that measure how controlling versus submissive one feels.
- **Emotional creepiness:** Refers to unpleasant impressions resulting from unpredictability and ambiguity of, e.g., situations and technologies. Also includes “eeriness” and “feeling of uncanniness”.
- **Empathy:** Measure of perceived empathy or emotional intelligence of AI systems and individuals’ own empathetic responses.
- **Enjoyment, pleasure:** Emotional constructs that measure joy, enjoyment and pleasure.
- **Fear/anxiety:** Comprises emotional constructs denoted as fear or anxiety.
- **General emotional response:** Refers to emotional constructs that broadly refer to emotional responses of a general sort and do not have an explicit positive or negative valence (as do “positive emotion” and “negative emotion”). This category includes, e.g., mood, emotional engagement, emotional trust, affinity, attachment, and love.
- **Hope:** Emotional constructs that measure hope.
- **Loss emotion:** Measures of an emotional experience of loss.
- **Negative emotion:** Refers to constructs that are intended to negative emotion in general – i.e., not referring to concrete emotions – and that explicitly refer to negative emotion.
- **Positive emotion:** Refers to constructs that are intended to positive emotion in general – i.e., not referring to concrete emotions – and that explicitly refer to positive emotion.
- **Sadness:** Emotional constructs that measure a state of sadness.
- **Safety:** Measures of a feeling of safety.
- **Regret:** Measures of feelings of regret.
- **Warmth:** Measure of perceived warmth, friendliness, helpfulness.
  Also covers social affability.

v08 Number of items used to measure the emotional constructs

The number of items used to measure the emotional constructs listed under v07.

Special cases:

- If different items are used in different studies within a single contribution to measure the same construct, the higher number is counted.
- Items for „cognitive empathy” are not included under empathy due to an explicit distinction between emotional and cognitive empathy (concerns Tsumura and Yamada 2023).
- If the same items are used to operationalize multiple constructs, all items used for each construct are counted (this concerns Downen et al. 2024, who use the same 15 items to measure to two scales, pleasantness and attentiveness).

IV Sample

v09 Sampling method

- **Convenience sample:** Refers to forms of convenience sampling, such as the use of online access panels like Amazon Mechanical Turk that do not use quotas or probabilistic sampling, the distribution of a survey among students, or the use of the snowball method.
- **Quota sample:** Refers to a sampling that uses predefined quotas based on known distributions in the target population.
- **NA:** The sampling method is not mentioned or cannot be inferred from the description of the research design.

v10 Sample size

Overall number of respondents in the relevant studies within a contribution. A single contribution can contain more than one study. Relevant studies are those studies in a contribution that examine emotional responses to or evaluations of AI systems.

v11 Mean sample size

The average sample size per relevant study in a contribution. Relevant studies are those studies in a contribution that examine emotional responses to or evaluations of AI systems.

v12 Countries

Text field containing the countries covered in a contribution.

If no country is mentioned and if it cannot be inferred from information provided in the study, "NA" is stated in the field.

V Scale formation

v13 Reliability test

Does the contribution use techniques for checking the reliability of a scale, such as Cronbach's α or different forms of factor analysis (including single factor test).

0 = no scaling method used

1 = Scaling method used

v14 Cronbach's alpha

Does the contribution use Cronbach's α to examine the reliability of scales for measuring emotional constructs?

0 = No

1 = yes

v15 Factor analysis and discriminant validity tests

Does the contribution use a form of factor analysis or test discriminant validity (such as examining the average variance extracted) to examine the reliability of scales for measuring emotional constructs?

0 = no

1 = yes

VI Antecedents and outcomes of emotional responses

General note: Control variables are coded among the independent variables if they are presented as a part of the main findings (e.g. regression tables) and only when clearly specified as predictors (including through hypotheses), not just as correlates. Moderating variables are also coded as independent variables if direct effects are reported.

v16 Emotion as independent variable

Are the emotional constructs measured in a contribution studied as an independent variable?

- no
- yes

v17 Dependent variables (text)

Free text field listing the dependent variables affected by the studied emotional responses in a contribution.

v18 Emotion as independent variable

Are the emotional constructs measured in a contribution studied as an independent variable?

- no
- yes

v19 Independent variables (text)

Free text field listing the independent variables influencing emotional responses studied in a contribution.

v20 Mediation

Does the study examine emotional constructs as mediating variables in a formal mediation analysis or at least a basic path analysis (inspecting the individual paths and interpreting them in terms of a mediation effect)?

- no
- yes

v21 Summary of findings (text)

Text field containing a brief description of the key findings concerning the emotional constructs investigated in a contribution. Only main effects are described.

v22 Dependent variables: behavior

Multiple mentions are possible. Only binary coding (1 = studied). If several constructs fall under the same category, this is coded as 1.

- **Cooperation:** Refers to measures that reflect cooperation or intention to cooperate with an AI system.
- **Disclosure willingness**: Refers to measures reflecting a willingness to disclose information about oneself.
- **Information verification:** Measures of the intention to verify information provided by an AI system
- **Involvement:** Refers to measures of a person's motivational attitude toward an object, stemming from the relevance and importance to the individual.
- **Objection:** Refers to measures of objection or resistance to AI systems or their use.
- **Recommendation:** Comprises measures that reflect the intention to recommend an AI system service, such as word of mouth intention, recommendation intention, and storytelling.
- **Spending:** Refers to the spending or intention of spending money for a service. Also includes support for public spending.
- **Unethical behavior:** Refers to measures of respondents being willing to engage or engaging in unethical behavior.
- **Use and intention to use:** Refers to measures that represent use, use intention or use continuance intention and related measures, such as exploration intention, reliance, measures of acceptance, such as job acceptance intention, loyalty, and the readiness to follow recommendations (as a form of use in terms of delegation).

v23 Dependent variable: evaluations

Multiple mentions are possible. Only binary coding (1 = studied). If several constructs fall under the same category, this is also coded as 1.

- **AI development:** Measures expressing support for AI development, e.g. through financing research with taxpayer money.
- **Attitude:** Comprises measures of general attitudes toward AI systems and AI-based services. Includes concrete attitudinal constructs such as cynical hostility.

- **Attitude toward and trust in organization:** Refers to measures that reflect attitudes toward or trust in the organizations deploying an AI system.
- **Coping strategy:** Measures of strategies for coping with demands that exceed one's resources.
- **Facilitating conditions:** Measures of perceived facilitating conditions of AI system deployment and use, such as technical and organizational infrastructure supporting the use.
- **Perceived anthropomorphism:** Measures of perceived human-likeness of AI systems.
- **Perceived uniqueness:** Refers to measures of the perceived uniqueness of how an AI agent treats a person and their needs, concerns and issues.
- **Reflection on teamwork:** Measures relating to changes in team processes and routines.
- **Satisfaction:** Refers to measures that relate to the satisfaction with an AI system or an AI-based service. Comprises, e.g., customer satisfaction, perceived service quality, user experience rating, and well-being.
- **Skepticism:** Refers to measures of an individual's disposition to doubt or question something.
- **Social attraction:** Refers to measures of how much individuals perceive an AI system to be personal or friendly. Note that this construct differs from warmth.
- **Social influence:** Measures of perceived social influence concerning AI use.
- **Task performance:** Measures of the task performance as rated by respondents.
- **Tolerance of service failure:** Refers to measures of the tolerance of service failures.
- **Trust in AI:** Comprises measures of trust in AI systems.
- **Uncertainty:** Refers to measures of perceived uncertainty regarding an AI system, its benefits and its risks.

v24 Independent variables: AI versus no AI

Multiple mentions are possible.

Refers to measures of a contrast between the use of an AI system versus no AI system use (e.g., human comparison) in a given setting.

v25 Independent variables: AI features

These features can refer to factual properties and the appearance of an AI system as well as to the perceived presence of these features.

Multiple mentions are possible. Only binary coding (1 = studied). If several constructs fall under the same category, this is coded as 1.

- **Agent type:** Refers to measures of the kind of AI system (such as a chatbot). This includes conceptual metaphors and depictions of AI systems (e.g., intelligent entity versus machine or different intelligence types) and properties like the degree of gamification that concern the nature or type of the AI application.
- **Autonomy:** Refers to measures of the degree of autonomy (in a weak sense) of an AI system. Includes the degree of automation.
- **Cooperation:** Refers to measures of the extent to which an AI system behaves in a cooperative manner with humans. Includes AI systems playing with or against humans (and defeating them).
- **Credibility:** Refers to measures of the credibility of an AI system, understood as the expectation that an entity will act in the way that it states it will.
- **Emotional and empathetic expression:** Comprises measures of an AI system expressing emotions or empathy toward users.
- **Entitativity:** Measures of the extent to which a group of individuals resembles or acts as a single entity.
- **Gender of the AI system:** Refers to measures of gender as a feature of an AI system.
- **Human-likeness:** Refers to measures of how much an AI system is anthropomorphized and human-like. This includes appearance as well as behavior, such as non-verbal cues.
- **Humorous response:** Refers to measures of whether an AI system emulates a humorous response or not.
- **Information content:** Refers to measures representing properties of the information or content produced by an AI system, such as risk messages or information valence.
- **Ingroup/self-similarity:** Comprises measures of the extent to which an AI system is treated or presented as a member of an ingroup. Includes perceptions of social similarity of an AI system and self-congruence.
- **Outcomes favorable:** Measures the degree to which AI systems produce favorable outcomes from the point of view of respondents. This also includes negative measures, such as being the target of discrimination and service failure.
- **Perceived risk:** Comprises constructs that measure the perceived risk associated with an AI system use.

- **Perceived status:** Refers to measures of the perceived social status of an AI system.
- **Service quality:** Constructs that measure aspects concerning the quality of a service provided by an AI system. This comprises, e.g., efficiency, responsiveness, personalization.
- **Transparency:** Refers to measures of the (actual or perceived) transparency of an AI system.

v26 Independent variables: respondent features

Multiple mentions are possible. Only binary coding (1 = studied). If several constructs fall under the same category, this is coded as 1.

- **Attitudes:** Refers to measures of attitudes relating to AI systems and their use. This also includes acceptance as a construct as well as concrete measures relating to AI use, such as privacy concerns and technology anxiety or technology optimism.
- **Job stress:** Measures of experienced job stress.
- **Motives:** Refers to motives of AI system use.
- **Personality:** Refers to measures capturing personality traits, such as openness, neuroticism, innovativeness, and sense of uniqueness.
- **Salient social group:** Refers to measures that reflect whether respondents feel part of a salient social group. This can comprise gender (which is then not coded as socio-demographics) if it is explicitly described and measured as a salient social group, e.g., as the object of decision-making.
- **Self-efficacy and experience:** Measures of respondents' perceived own efficacy in using AI systems or AI-based services. Includes prior use experience and use frequency.
- **Social influence:** Comprises measures reflecting the influence of other persons or social norms on respondents.
- **Socio-demographics:** Refers to sociodemographic variables, such as sex, age, and education.
- **Trust:** Comprises measures of trust in an AI system.

v27 Independent variables: Task properties

Multiple mentions are possible. Only binary coding (1 = studied). If several constructs fall under the same category, this is coded as 1.

- **Area/Domain:** Refers to measures of domains of AI use.
- **Failure attribution:** Measures of whether a failure at performing a task is attributable to an AI system or a human.
- **Hedonic versus non-hedonic:** Refers to measures capturing a contrast between hedonic and non-hedonic tasks.
- **Mechanical versus social/human:** Refers to measures capturing a contrast between mechanical tasks versus tasks that require human or social capabilities.

- **Medical condition:** Refers to measures reflecting medical conditions of respondents.
- **Observing versus teaching AI:** Refers to measures reflecting a contrast between observing an AI system performing a tasks versus teaching the system to perform the task.
- **Service type:** Refers to measures of different service types involving AI use.

v28 Contrasting emotional and cognitive dimensions or mechanisms

In the general discussion and conclusion, does the contribution explicitly contrast an emotional dimension or mechanism with a cognitive one? Also includes the distinction between a central and peripheral channel of information processing.

0 = no

1 = yes

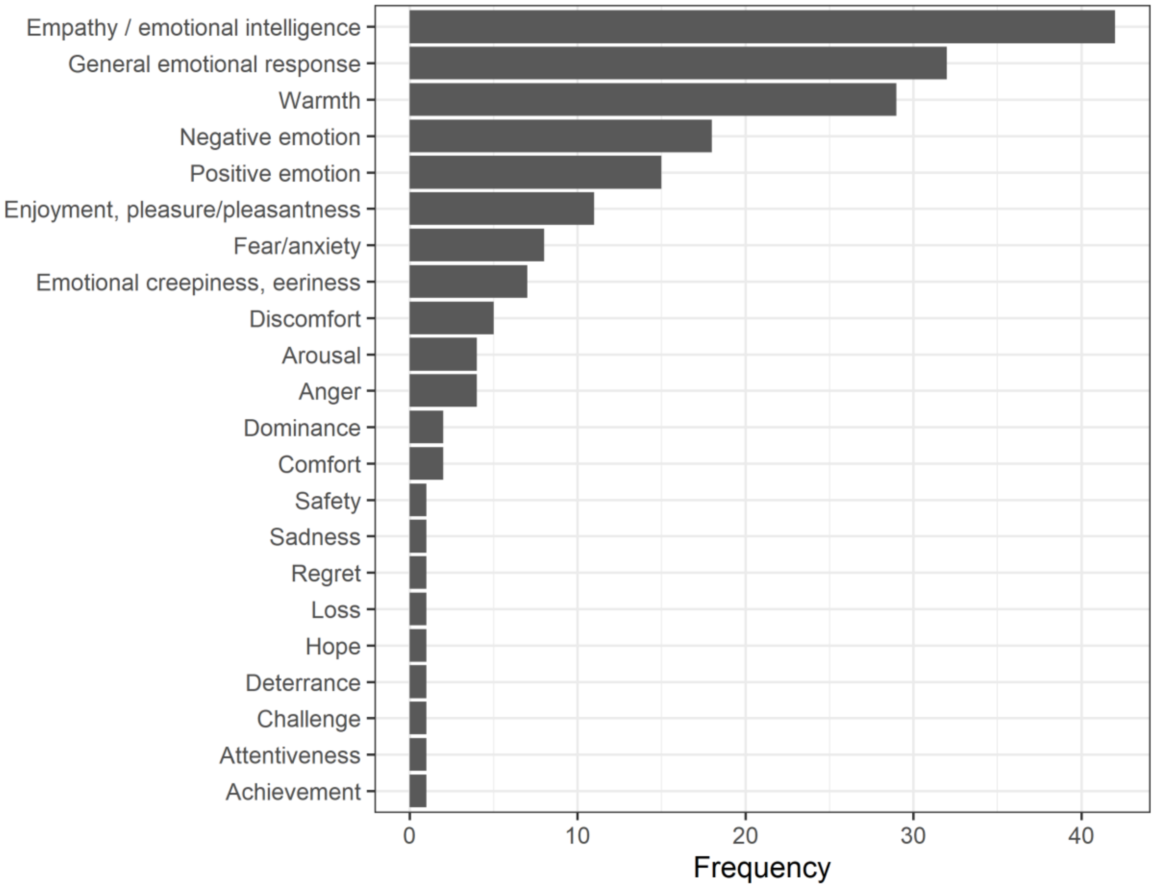
v29 Discussing implications for responsible AI use

In the general discussion and conclusion, does the contribution discuss the relevance of the findings with regard to responsible AI use, i.e., with regard to ethical implications and consequences for social values? Coding as “yes” requires more than the mere mention of ethics or social values. A contribution must establish a link between study results and consequences for ethics and social values.

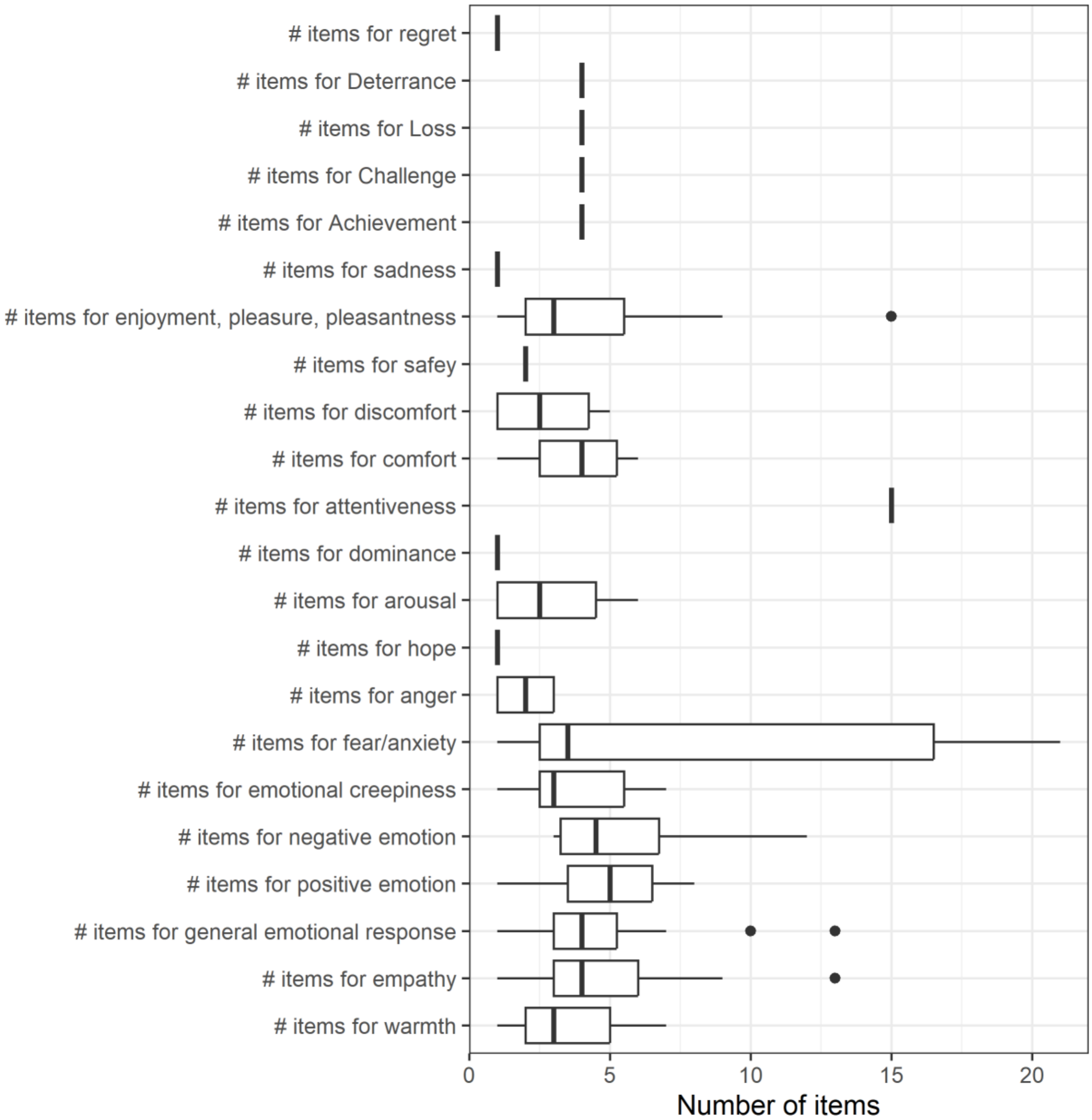
0 = no

1 = yes

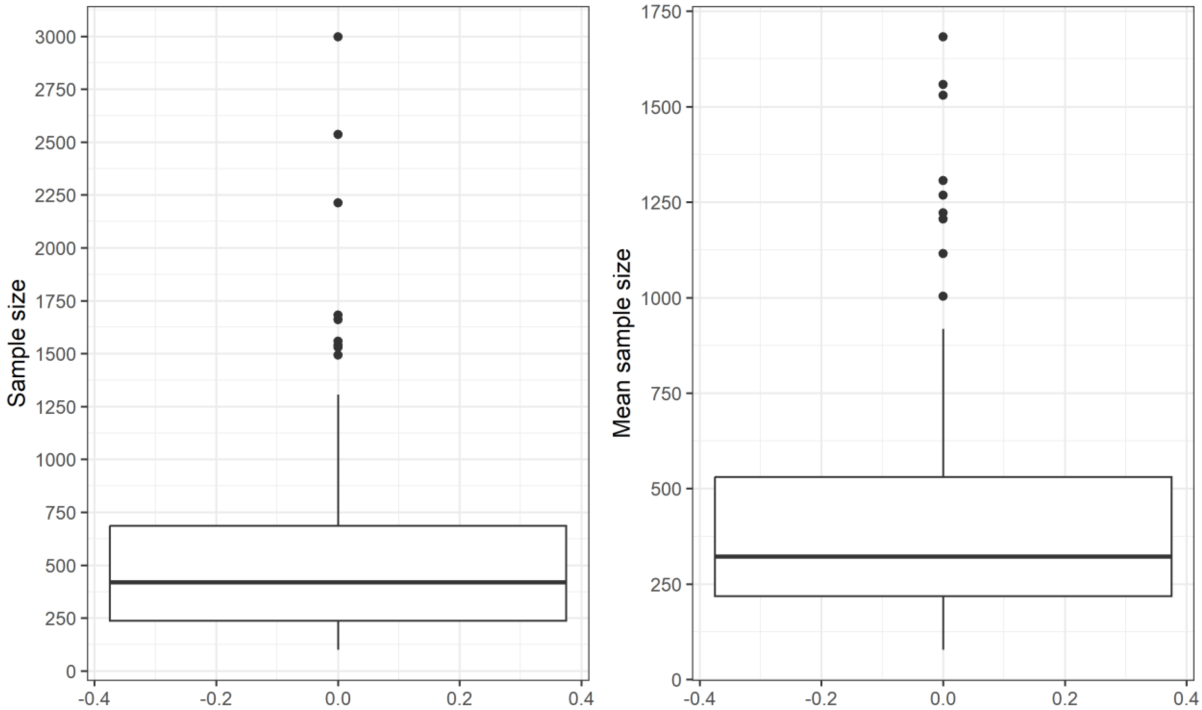
Appendix A6: Emotional constructs covered in the reviewed contributions



Appendix A7: Number of items used to measure the emotional constructs



Appendix A8: Number of observations per contribution and study



Notes: Sample size in the left-hand chart represents the overall number of observations in a contribution, which can be the sum of observations from several studies within a single contribution. Mean sample size on the right-hand side refers to the average number of observations over all studies within a contribution. Only those studies within a contribution are included in the count that use measures of emotional responses.