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Customer delight in AI-driven services

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ABSTRACT

The presence of Artificial Intelligence (AI) in the service context is bursting forth in numerous applications, leading customers to experience emotional reactions in important ways that have strategic implications for marketers. In this research, we reconceptualize the construct of customer delight in AI service interactions. Drawing on previous frameworks and seminal literature about AI service, customer delight, and literature on emotions, we applied a multimethod approach to unveil the elements of customer delight in AI service interactions, build a useful, novel scale to measure it, and test its effects on key relevant marketing outcomes. We also shed light on which aspects of customer delight are most relevant for different types of AI services. Finally, we give practical suggestions to managers and practitioners on how to make AI services delightful, drawing a useful roadmap in a rapidly evolving landscape.

1. Introduction

If you are running a business, chances are that AI is one of the topics on your agenda. AI can be defined as machines that exhibit aspects of human intelligence involving technologies that can learn, connect, and adapt (Huang and Rust, 2021). AI is becoming increasingly relevant from a business perspective and is experiencing remarkable growth. The AI market is projected to reach $243.70 billion in 2025, with revenues expected to grow at a compound annual growth rate (CAGR) of 27.67 % between 2025 and 2030, resulting in a total market volume of $826.70 billion by 2030 (Statista, 2024). Also, from a service perspective, AI shows great potential with increased adoption of AI technologies by various industries, including healthcare, finance, and retailing, among others. Indeed, one of the things that is quite interesting to notice about AI, especially from a consumer behavior perspective, is its unique connection with service. Since AI performances are connected to the idea of automation, production of an output, and delegation (Puntoni et al., 2021), AI applications fit very well with the service industry, and AI service applications may have a wide palette of forms. This is also supported by service literature, which refers even to (physical) products like Alexa or Roomba as examples of AI services (Huang and Rust, 2021).

One example that dramatically reveals the dynamics and benefits of AI implementation in services is provided by IKEA's adoption of AI solutions. IKEA, a Swedish company selling worldwide, specializes in marketing furniture and household items. IKEA will be used herein to illustrate important service features and elements revolutionizing marketing practices and delighting customers (Pontefract, 2016). Although IKEA is primarily a furniture retailer known for a distinctive in-store experience, it sees technology as key to enhancing customer interaction. Over the years, it has adopted several tech innovations to transform its service experience. Three standout AI tools reflect this shift: (1) an AI-powered recommendation system, (2) IKEA Kreativ, and (3) the IKEA AI Assistant. In 2021, IKEA introduced the first AI tool to improve e-commerce by offering real-time, personalized product suggestions, boosting click-through and order values (Kenyon, 2021). In 2022, it launched IKEA Kreativ, a mixed-reality app letting users design 3D home spaces, try out furniture virtually, and share ideas (INGKA, 2022). Its goal is to offer an intuitive and inspiring design experience (IKEA, 2019; INGKA, 2022). Most recently, in 2024, IKEA unveiled its AI Assistant, a generative chatbot providing product info and personalized design tips, aiming to democratize planning services and improve everyday life (INGKA, 2024; Marr, 2024). This journey by IKEA is an exemplary case of a company trying to evolve its services through the development of

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new technologies to effectively address changing consumer behaviors. IKEA proposed new technological interactions to complement their traditional touchpoints (Lunden, 2017) and to align practices to the evolution of different consumer needs and customer journeys (INGKA, 2022; Marr, 2024; Stackpole, 2021). This shift is also connected to AI development. Users are becoming increasingly comfortable with technology, and the experiences that AI introduces in terms of convenience, personalization, and more generally, the improvement of the experience of daily tasks, create a synergistic fit between technological abilities and consumer needs (Statista, 2024).

In this environment, characterized by technological advancements and changing customer needs, AI introduces new, exciting opportunities and peculiar types of service interactions. For example, as AI has human-like abilities, users can perceive AI even as magical (Tully et al., 2025). Therefore, we argue that effectively designed AI services, due to their innovative features, "magical" abilities, and wide range of customer benefits, have the potential to elicit customer delight. Although there are multiple approaches concerning its conceptualization and definition, customer delight is mainly referred to in literature as a profoundly positive emotional state, generally resulting from having one's expectations met and even exceeded to a surprising degree (Oliver et al., 1997; Rust and Oliver, 2000). It is a construct widely studied in traditional service contexts (e.g., for concerts or websites – Bartl et al., 2013; Finn, 2005; Oliver et al., 1997) and promoted by practitioners in the 1990 s under the assumption that merely satisfying customers may not be enough to create demand and gain a competitive advantage. The positive impact of delight is documented in scientific research (e.g., Bartl et al., 2013), and recent managerial literature explicitly emphasizes the unique benefits of delighting customers (Bisht et al., 2024).

Despite evidence about the positive effects of delight and its prevalent conceptualization as an emotional state (Finn, 2005), the presence of multiple definitions of customer delight calls for a question that has been recently raised in the delight literature and that deals with understanding what delight actually is. Parasuraman et al. (2021) answered this question through a comprehensive idea of delight that includes not only emotions but in addition other complementary service properties that characterize a delightful experience (e.g., the ability expressed by the service provider to solve problems or consumers' perceived control). Taking cues from Parasuraman et al. (2021), we argue that a similar approach, along with a new conceptualization of customer delight that acknowledges the unique characteristics of AI service interactions, is needed. That is, because AI service experiences differ significantly from the traditional contexts in which previous research has examined delight, this calls for a new approach. For example, the interaction between a human agent and a non-human one can be very different from a typical interpersonal exchange that we encounter in traditional customer service contexts. Indeed, consumers tend to feel less judged by a robot (rather than by a human) when having to engage in an embarrassing service encounter (Holthöwer and Van Doorn, 2023) and tend to respond better to worse-than-expected offers when they are provided by an AI agent rather than by a human one (Garvey et al., 2023). Also, service AI brings new types of capabilities (Huang and Rust, 2021), leading to customer-AI complex interactions, which can involve a wide range of consumption aspects, from functional ones to those connected to the self. For example, Puntoni et al. (2021) argue that customers can be empowered by AI: they can delegate less relevant tasks to AI and focus on what is more meaningful to them. A similar concept is called augmentation, according to which AI and users can combine their intelligence and relative strengths to mutual advantage (Hoffman and Novak, 2018; Huang and Rust, 2022). For example, if Netflix can suggest movies that match a user's tastes, the user gains the ability to select films that better meet their needs and to expand their movie knowledge through improved recommendations. As a result, the user's capacity to have a satisfying viewing experience and to develop film expertise is enhanced through participation in the user-algorithm duo (Hoffman and Novak, 2018).

The problem of a new conceptualization of delight is connected to the issue of developing a measurement of the construct (Barnes and Krallman, 2019). This is particularly the case when the construct is involved in a peculiar, novel, and dynamic context as the AI one. As explained before, AI services have the potential to expose customers to experiences that are new in the service realm (e.g., interacting with robots vs. human-service providers; Garvey et al., 2023). In such a context, it is crucial for researchers and managers to have a measure that accounts for both the affective experience and the appraisal of delightful elements, while also considering the unique aspects of an AI-driven delightful experience. For example, for a service like streaming platforms that have an AI-based recommendation system, measuring delight solely through its affective component (e.g., Finn, 2005) gives insights only about how the customers react emotionally, neglecting their reactions to other paramount aspects of the service experience: is the delight connected to the personalization process? Or is the delight, instead, connected to identity-based consumption of content? A scale that relies on a multidimensional structure of delight can give a more comprehensive and holistic image of delight AI experiences. This is particularly the case for such a novel branch of services like the AI-powered ones. Indeed, unlike traditional services, providers of AI-based services cannot rely on decades of established market traditions. Therefore, we argue that the holistic approach proposed by Parasuraman et al., (2021), which explicitly takes into account the nature of potentially delightful elements, is necessary to understand the construct of delight as well as to develop a practical tool to measure it.

In sum, there is a wide palette of interaction elements that are connected to AI services that differ from the contexts in which delight has been examined in the past. Therefore, we argue that in such a distinctive and dynamic context, a different conceptualization of customer delight is needed to understand what a delightful experience in the AI service interaction is. Consequently, we aim to answer the following research question: What does it mean to delight customers in AI service interactions? To do so, we conducted several studies that correspond to two main objectives connected to this foundational research question. The first objective is to build a new conceptualization of customer delight in AI service interactions, develop a corresponding measure, and assess the impact of customer delight on key marketing outcomes (Studies 1–6). In particular, we reconceptualize customer delight based on the concept of the syndrome used in psychology (Averill, 1982), according to which emotions are complex constructs composed of emotional components, as well as the appraisal of the emotional stimuli and their personal and social meaning to consumers. Once we established the structure of delight in the AI service context, we further tested the behavior of the delight syndrome in the interaction with different AI services. Along this line, the second objective is to test the ability of our delight structure to acknowledge the variation in customer delight depending on different AI service interactions, namely, based on mechanical vs. thinking vs. feeling intelligence (Huang and Rust, 2021), through a multigroup comparison study (Study 7). Each objective also has a distinct contribution. The first objective of this work contributes to the delight literature (Oliver et al., 1997) and AI service literature (Bagozzi et al., 2022). Instead, the second objective contributes to AI intelligence theory (Huang and Rust, 2021) and proposes further practical implications for AI service companies.

The results of our studies reveal that customer delight in AI service interactions reflects several dimensions that deal both with emotional responses, as well as appraised positive elements of the interactions with AI services, and it positively impacts managerially relevant outcomes (i.e., word of mouth–WoM, intention to continue to use, tolerance of failure). Also, the relevance of the dimensions varies across different types of AI (Huang and Rust, 2021). In doing so, this work contributes to the literature in several ways. It contributes to the literature of AI service interaction (e.g., Bagozzi et al., 2022; Blut et al., 2024) and customer delight (Barnes and Krallman, 2019) by developing a new conceptualization and a new measure of customer delight that acknowledges the peculiar characteristics of AI service interactions. It also contributes to the AI intelligence theory (Huang and Rust, 2021) by proposing further insights about the appraisal of AI service interactions and their contribution to customer delight, with variations across different types of intelligence.

2. AI in service

IKEA is just one of many companies that have implemented AI in the design of their service experiences, and this single case illustrates the variety of ways companies can adopt AI. The IKEA example also reflects the service-nature of AI, and how AI services can have multiple and different forms. To systematize the plethora of situations present in the real world, Huang and Rust (2021) have developed a framework identifying three types of AI: mechanical, thinking, and feeling.

The three types of AI are cumulative; each one shares the characteristics of the simpler one, yet has some specific characteristics of its own. Mechanical AI is the simplest type, while feeling AI is the most sophisticated. Mechanical AI learns and adapts only to a minimal degree, and its primary advantages are standardization and automation. Indeed, given its mechanical capabilities, it is mainly applied in service delivery to guarantee high efficiency for service providers and convenience for customers (Huang and Rust, 2021). Two examples of mechanical AIs are service robots and automatic kiosks.

Thinking AI, in addition to mechanical AI capabilities, can also analyze big data and, based on that, make intuitive decisions for managers. Its primary advantage is personalization (Huang and Rust, 2021; Scholdra et al., 2023). Indeed, it is mainly used for service creation, as it can support companies in creating valuable and appealing services uniquely for each customer. Netflix's and IKEA's recommendation systems are examples of services based on the capabilities of thinking AI.

Finally, feeling AI can learn from each customer's experience. This means that feeling AI can also analyze and make intuitive decisions based on both individual- and context-specific data. Therefore, its primary advantage is relationalization (i.e., personalized relationship enhancement; Huang and Rust, 2017; 2018). Indeed, it is mainly used for service interaction as it can allow companies to adapt their communication with customers based on everyone's experience, emotions, and situation (Huang and Rust, 2021). There are two types of feeling AIs: a low-end feeling AI, which mainly deals with basic customer service, and a high-end feeling AI, with machines that have room for empathy and understanding in a customer care setting (Huang and Rust, 2024). The difference between these two types of feeling AI is also characterized by its current availability in the marketplace. Indeed, low-end feeling AI is already present in the current technological landscape and widely available to the public: voice assistants like Alexa and Siri are examples of services based on the capabilities of low-end feeling AI. On the other hand, by contrast, high-end feeling AI with more dynamic and tailored capabilities is still emerging and not yet fully available to the mass market (Huang and Rust, 2024; Liu-Thompkins et al., 2022).

Even though feeling AI is the most sophisticated type and the most effective in eliciting customer positive emotions (Schepers et al., 2022), choosing to implement it over other types might not always be the best decision to improve the service experience (Choi et al., 2021; Juquelier et al., 2025). Indeed, the choice of which AI type to implement in the design and offer of service experience is critical for the success of the service, and it depends on situational factors, such as service failure (Choi et al., 2021), time pressure (Juquelier et al., 2025), stage of the service process (Huang and Rust, 2021), and characteristics of the service such as service tier (low-cost vs. full-service; Schepers et al., 2022). Therefore, service providers should ask themselves not only whether to seize the opportunity to implement AI, but also which types of AI should be adopted and how they should be implemented in the design of the service experience. These questions are central for companies, considering their business needs to design a service experience able to delight their customers (Bisht et al., 2024; Parasuraman et al., 2021). However, designing delightful service experiences is not only a creative effort, but it also requires an accurate understanding of the meanings of customer delight in AI service interactions. With this type of information, it is possible to link AI service design with the elicitation of customer delight and to reach relevant marketing outcomes, such as WoM or intention to continue to use.

3. Customer delight

Delight is narrowly defined as something that gives great pleasure, joy, or gratification (Merriam-Webster Dictionary, n.d.). The idea of delighting customers has also been studied in the service setting and has been examined in the managerial literature as well as in scientific papers (e.g., Oliver et al., 1997). Several researchers have studied the role of this construct in consumption and its positive impact (e.g., Rust and Oliver, 2000). For example, previous work has found that delight can be elicited both by primary attributes (Bartl et al., 2013) and secondary attributes of a service (Arnold et al., 2005; Beauchamp and Barnes, 2015; Wang, 2011). Also, delight can be linked both to utilitarian (Bartl et al., 2013) as well as hedonic consumption experiences (Chitturi et al., 2008). Once customer delight is elicited, it can lead to positive consumer reactions, such as willingness to pay, WoM, or repurchase intention (e.g., Chitturi et al., 2008; Choi et al., 2024; Kim et al., 2024; Wang, 2011).

From a theoretical perspective, three different approaches can be identified that deal with the definition of customer delight, as well as its measurement: an attitudinal approach, an affective approach, and a motivational approach (Torres and Kline, 2013; Torres and Ronzoni, 2018; Torres et al., 2020). These three streams are further summarized in Table 1.

One school of thought sees delight as an attitude (see Table 1) and adopts an attitudinal approach towards the construct. This approach has its roots in service practice and theoretically relies on past theories connected to satisfaction, such as the confirmation-disconfirmation theory (Oliver et al., 1997) and the zone of tolerance perspective (Zeithaml et al., 1993). In particular, this school of thought claims that a service that meets customer expectations makes them satisfied, whereas exceeding their expectations makes them delighted (Barnes and Krallman, 2019). The main implication of this point of view is that delight and satisfaction are both considered attitudinal (i.e., evaluative) in nature and strongly connected, to the point of considering the former an extreme level of the latter (Kim et al., 2015; Torres et al., 2020). This perspective is also supported by the way delight has been measured in past research. For example, Kumar and Iyer (2001) conceive delight as an evaluation or attitude and measure it with rating scales from 1 (completely dissatisfied) to 10 (completely satisfied), according to which customers are considered "delighted" when giving 9 or 10 ratings.

A second stream of research sees delight as the satisfaction of needs (see Table 1) and embraces a motivational approach towards the construct. This approach has been introduced by Schneider and Bowen (1999), who in their seminal work criticize the idea that delight is the result of exceeding expectations, highlighting the limitations of such an approach. For example, it is difficult to identify expectations validly, and they can vary based on personal reasons. Therefore, they propose that delight should be elicited by the satisfaction of personal needs, like self-esteem (Torres and Kline, 2013). This approach has implications in terms of measurements of the construct as well. For example, the scale developed by Torres and Ronzoni (2018) has several items that reflect the motivational approach towards delight (e.g., "I felt special").

Lastly, another stream of literature sees delight as an emotion (see Table 1) and adopts an affective approach towards the construct (e.g., Kumar et al., 2001). This school of thought builds on the work of Plutchik (1980) that conceptualizes delight as composed of joy, a basic emotion, and surprise, an orientation reaction. One of the main aspects emphasized by this approach is that delight and satisfaction do not exist on the same continuum but, instead, comprise two completely different

Table 1
Customer delight conceptualizations.

Delight conceptualization	Definition	Example of operationalization	Examples of industries of application	Theoretical roots	Key references
Delight as an attitude	Delight is an extreme level of satisfaction, and exists above the "zone of tolerance" (Barnes and Krallman 2019; Torres and Ronzoni 2018; Torres et al., 2020).	Kumar and Iyer (2001) asked respondents to report the overall satisfaction of a service on a scale from 1 (completely dissatisfied) to 10 (completely satisfied). Respondents who reported 9 or 10 were considered delighted customers.	• Automobile dealership (Kumar and Iyer 2001) • Tourism (Füller and Matzler 2008) • Phone Network Service (Roberts-Lombard and Petzer 2018)	Theory about the zone of tolerance (Zeithaml et al., 1993).	Keiningham et al. (1999)Kumar and Iyer (2001)
Delight as the satisfaction of needs	Delight is connected to the fulfillment of relevant and specific needs (Torres and Ronzoni 2018; Torres et al., 2020).	Torres and Ronzoni (Torres and Ronzoni 2018; Torres et al., 2020) developed a delight scale that includes several items that take into account the motivational perspective of delight: - I felt special - I felt welcomed - I felt acknowledged - I felt like a unique customer	• Hotel (Torres and Kline 2013; Torres et al., 2024) • Restaurant (Torres et al., 2024) • Medical services (Clemmer and Schneider 1996)	Theory on human needs (e.g., Maslow 1943).	Schneider and Bowen (1999) Kwong and Yau (2002)Torres and Kline (2013)
Delight as an emotion	Delight is a profoundly positive emotional state (Barnes and Krallman 2019; Torres et al., 2020).	Finn (2005) measures delight through three items connected to emotional states: - Delight - Elated - Gleeful	• Hotel (Choi et al., 2024; Kim et al., 2024) • Retail (Arnold et al., 2005) • Restaurant (Barnes et al., 2016)	Theory on emotions (Plutchik 1980).	Kumar et al. (2001) Finn (2005)Finn (2012)
Reconceptualization of customer delight as a syndrome of multiple concepts	**Delight reflects a customer's intense positive emotional response associated with a set of appraised positive elements of the interactions with AI services.**	**"Customer delight in AI service interactions" scale:** **- Self-enhancement** **- Self-improvement** **- Self-expansion through an agentic partner** **- Convenience** **- Transparency** **- Personalization** **- Human-like relationships** **- Ease of use** **- Positive affect-high arousal** **- Positive affect-low arousal**	**• AI-based services**	**Constructivist view of emotions (Averill 1982).**	**Current research**

constructs, with different antecedents, outputs, and measurements, or can even occasionally co-occur in the same framework (e.g., Krallman et al., 2023). Although the stream of research linked to the affective conceptualization of delight is not without debate, particularly regarding the role and necessity of surprise in eliciting delight (e.g., Kumar et al., 2001; Ma et al., 2013), this perspective remains arguably the most popular of the three approaches. We should not be surprised, therefore, that the scale developed by Finn (2005), which measures delight through three affective items (i.e., "delight", "elated", "gleeful"), is widely used and adapted in service research.

Despite these three clear streams of thought, the conversation about the definition of customer delight is still an ongoing discussion. For example, in a recent contribution based on three qualitative studies, Parasuraman et al. (2021) presented a comprehensive conceptualization of customer delight in the service context that includes, in addition to positive emotions, five additional distinct service "properties" characterizing delightful customer experiences. Achieving customer delight generally involves, based on the suggestions of Parasuraman et al. (2021), the following content: positively valenced emotions, interactions with other customers and employees, successfully solving the customer's problem during the service encounter, linking the experience to nostalgia and engaging various senses, a range of duration including quick versus prolonged timing, and finally the customer feeling a sense of control/agency.

Given that positive emotions play an essential role in shaping customer delight, the additional five "properties" complement and help interpret such emotional responses. We recognize the potential of this comprehensive perspective for the investigation of customer delight in AI service settings, which is also in line with previous research that acknowledges the presence of multiple dimensions or versions of delight (e.g., Torres and Kline, 2013). Service providers need to understand which specific AI service elements evoke profoundly positive emotional states, and thus how to optimize their offers with multiple AIs. Without such knowledge, service providers cannot expect such behavioral outcomes as loyalty or WoM as desired responses to their service offers.

Therefore, starting from the qualitative insights of Parasuraman et al. (2021), we continue in this stream of work by contextualizing it in the AI service setting. To do so, inspired by a constructivist view of emotions (Averill, 1982), we conceptualize delight as a syndrome that includes a customer's intense positive emotional response associated with a set of appraised positive elements of the interactions with AI services (see Table 1–bottom row). This new conceptualization also calls for the development of a new, specific measurement scale. Indeed, the problem of conceptualization in the delight literature is strictly connected to the problem of measurement (Barnes and Krallman, 2019). Thus, to better understand the complexity of customer delight in AI service interactions and inform the development of a reliable measure, we introduce the conceptualization of customer delight as a syndrome, before demonstrating its validity and usefulness empirically.

4. Delight as a syndrome

A syndrome is defined by Averill (1980, p. 307) as a "set of responses that covary in systematic fashion". The variety of different response types that constitute a syndrome is configured or organized in a pattern or structure. It is the structure as a whole that functions as an explanatory framework, not the individual elements (Jaworski, 2016). A syndrome is similar in meaning to the notion of a prototype as used in cognitive psychology (Rosch and Mervis, 1975) and marketing research (Bagozzi et al., 2017; Batra et al., 2012). Detailed arguments on the meaning and usefulness of structural concepts can be found in Bagozzi (2022, 2026).

Taking a constructivist view of emotions, Averill (1982, p. 4) suggests that emotions can be viewed as socially constituted syndromes "which include a person's appraisal of the situation, and which are interpreted as passions (things that happen to us) rather than actions (things we do)". The appraisal of the emotional stimuli and the affective responses are the two most important elements of a syndromic conception of emotion, and any specific emotion refers to the way the constituent elements are organized and the function they serve in relation to consequent behaviors.

To conceptualize customer delight in AI service interactions as a syndrome has several advantages. First, in addition to the positive affective responses typically associated with the operationalization of customer delight (among others, Finn, 2005; Bartl et al., 2013), appraisals contribute to the syndromic conception of customer delight. Therefore, the appraised positive elements of AI service interactions become part of the emotion, not something antecedent to it. This point of view was proposed by Frijda (1986), who maintained that emotions encompass the designation of a number of processes transpiring from exposure to emotion-inducing stimuli (e.g., event coding, appraisal, action readiness) through arousal and action tendencies. Consequently, these appraised elements emerge as an important criterion for distinguishing delightful encounters in an AI service setting and their characteristics. This association between emotion descriptors and specific AI service interaction elements goes beyond the classic affective approach to customer delight and tries to incorporate how the affective reactions are experienced. Second, it is possible to recognize that customer delight in AI service interactions can be reflected in different combinations of psychological response types, with specific roles depending on several aspects, like the type of AI involved in the service or specific circumstances. This particularity allows researchers and practitioners to recognize the variety of possible AIs used in service to engage customers (Huang and Rust 2021) and their different contributions to the customer delight construct. Third, a syndromic conception of customer delight can better present the power of the different psychological response types and their organization to convert situations (e.g., customer encounters with AI service offers) into customer-relevant behaviors such as intention to continue to use the service or intention to spread positive WoM.

Therefore, acknowledging the work of Parasuraman et al. (2021) and considering the syndrome approach of Averill (1982), we start the empirical program by answering the first objective of the research, that is, to develop a new conceptualization and a comprehensive measure of customer delight in AI service interactions and to assess its impact on key marketing outcomes.

5. Developing a new conceptualization and measure of customer delight in AI service interactions (Studies 1–6)

5.1. Study 1: Identifying the elements of customer delight in AI service interactions

To operationalize customer delight in AI service interactions and translate it into a measurement scale, we started the empirical program with a qualitative study, which led to the identification of the elements of customer delight in AI service interactions and the development of a preliminary structure of the construct.

5.1.1. Participants and procedures

Ninety-two adult respondents (56 females, 33 males, 3 non-binary respondents, age: M = 33.02, SD = 13.00) obtained by snow-ball sampling procedures in two countries (the U.S. and Italy) participated in an online qualitative survey. The data collection strategy was based on two criteria. First, we continued gathering data until the saturation point was reached (Thomson, 2011). Second, we considered the usual sample that methodological guidelines recommend for qualitative online surveys (Braun et al., 2021).

A qualitative online survey was conducted using an adaptation of the critical incident technique (CIT; Gremler, 2004) to gain "understanding of the incident from the perspective of the individual, taking into account cognitive, affective, and behavioral elements" (Chell, 1998, p. 56). Respondents were asked to recall and describe a recent episode about a positive interaction with an AI-enabled service in which they experienced delight. After the data collection ended, episodes were collected in a document of 40,362 words. Respondents reported their experiences with several types of AI services that deal with mechanical intelligence (e.g., smart watches, a robot that prepares drinks), thinking intelligence (e.g., recommendation algorithms, AR, VR), and feeling intelligence (e.g., voice assistants) (Huang and Rust, 2021).

Following the idea of a structure of customer delight as a syndrome, we analyzed the data looking separately for the appraisals of the elements of the interactions with AI services as well as the affective experience attached to it. Concerning the appraisal of elements of such interactions, participants' responses were analyzed, taking cues from the grounded theory approach (Corbin and Strauss, 1990), the Gioia Method (Gioia et al., 2013), and their previous applications in marketing research (Nunes et al., 2021). We coded the data in three steps to ensure that empirical observations were "connected to extant theoretical ideas to generate novel conceptual insight and distinctions" (Langley et al., 2013, p. 11). Two authors (Coder A and Coder B) worked on the coding process. Both were highly familiar with literature about AI consumption (e.g., Puntoni et al., 2021), service AI (e.g., Huang and Rust, 2021), and customer delight (e.g., Oliver et al., 1997).

First, similar to the "open-coding" process (Corbin and Strauss, 1990), we analyzed each response at a level of analysis that was as close as possible to the way it was voiced by the participant. Coder A and Coder B worked independently on two different sections of the dataset while still discussing together potential doubts and issues. Second, similar to the process of "axial coding", we applied a theory-centered approach (Magnani and Gioia, 2023) to start to identify significant themes. We actively sought theoretical relationships between the excerpts extracted from the first round of coding to reach a higher level of abstraction and identify relevant concepts. In this phase, we organized the data taking also cues from previous literature about customer delight (e.g., Parasuraman et al., 2021) and AI (e.g., Puntoni et al., 2021). Coder A developed a set of themes used to code about 70 % of the critical incidents collected. The coding structure was then proposed to Coder B and discussed, focusing on how to address the part of the coding where agreement was lacking to ensure a rigorous and reliable coding process. Once this process was completed, Coder B coded the rest of the dataset and revisited the whole dataset if modifications in the coding were needed as a result of the analysis of the data. Possible modifications and integrations of the themes were discussed between the coders. The final set of themes was discussed with the whole research team. This process resulted in the identification of the main themes connected to the customer interactions with AI services, which were organized into major dimensions (elements), relying on past literature.[1] In this phase, the two coders worked together and discussed the overarching dimensions and the overall coding structure with the whole research team.

5.1.2. Results

The final elements connected to AI service interactions are described below. The coding scheme is available in Supplementary Materials (Figure I).

Self-enhancement. One element that emerged from the data was self-enhancement, which is about the perception that customers have about the way AI technologies can enhance their image and the way customers see themselves. Delighted respondents mentioned that when they use and interact with an AI service, they feel proud of themselves and see themselves as prestigious, cool, and part of an elite. This element relates to the idea of extended-self proposed by Belk (1988), according to which customers' possessions reflect and contribute to their identity. Self-enhancement is a kind of self-identity.

Self-improvement. Another element was self-improvement in a utilitarian sense. Similarly to what has been conceptualized by Puntoni et al. (2021) and Hoffman and Novak (2018), delighted respondents wrote about the fact that, by using AI services, they improve themselves and benefit from new possibilities and knowledge that they could not access autonomously, from discovering new music to being updated about their own health condition. In more detail, customers reported that they were delighted when they were able to improve their performance by using AI services. For example, thinking about a moment when they felt delight, respondents mentioned when they acquired new skills or improved existing ones, or when they expanded their knowledge and preferences thanks to the usage of AI services (e.g., recommendation systems such as Netflix or Spotify).

Self-expansion through an agentic partner. Another element that is part of delightful AI experiences is the self-expansion through an agentic partner. Indeed, customers perceive that AI devices are not passive entities. In delightful AI experiences, respondents appreciated the fact that the AI is perceived as able to learn and adjust. The AI service can autonomously start an interaction or task, and sometimes customers perceive the AI service to satisfy a need of theirs even before they perceive it or manifest it fully. This theme is in line with the idea of agency, autonomy, and authority that smart objects can have. As Hoffman and Novak (2018) propose, these agentic and autonomous abilities that an AI service may express can lead customers to a process of self-expansion, according to which the abilities of the customer are expanded as they are part of a relationship with the AI.

Human-like relationships. Another element was connected to the human-like relationship that a customer can develop with AI services, which is an important topic in the human–computer interaction literature (Hermann, 2022; Novak and Hoffman, 2019). Delighted respondents wrote that AI services can have human-like personalities and traits, enabling customers to experience human-like relationships. For example, respondents referred to virtual assistants as friends or companions and emphasized their ability to keep them company when they are alone. Also, respondents reported the fact that AI services have human-like abilities and behaviors, but also a human-like interaction style (e.g., a service robot in a restaurant asking the guests if everything is ok), which could lead to exciting, funny, or warm interactions.

Convenience. A fifth element was convenience, which is about the ability of AI services to make the lives of customers easier in effective and efficient ways. Similar to what is claimed by previous literature about AI (e.g., McLean and Osei-Frimpong, 2019) and delight (e.g., Parasuraman et al., 2021), delighted respondents wrote that AI technologies can simplify and help users in their everyday tasks. Respondents also emphasized AI's abilities to get things done accurately and in an efficient (i.e., timesaving) manner. Lastly, the multi-functional nature of some AI service solutions was mentioned.

Ease of use. A sixth element was ease of use, which is about the perceived ability of AI services to be easy-to-use and accessible to a wide range of people (e.g., Berman, 2005; Davis, 1989; McLean et al., 2021). Delighted respondents emphasized how it can be easy to use/interact with an AI service (e.g., using the voice instead of typing). According to several respondents, this process allows AI services to be accessible to a wide range of customers, even for those who may face difficulties when interacting with technologies (e.g., blind people or the elderly; Hermann et al., 2024).

Transparency. Another element that emerged, that echoes preliminary evidence from previous human–computer interaction research (Murtarelli et al., 2021), was transparency, i.e., the idea that delighted customers can understand how the system works and how the data are collected and used. Also, respondents perceived and emphasized their own benefits from the data collection process. In a delightful experience, customers can see how the data is tracked and also how this can bring value to their experiences (e.g., respondents reported understanding that an algorithm keeps track of their product search to suggest items that may be relevant to them).

Personalization. Several respondents discussed personalization, which is the perceived capability of AI services to understand user needs and preferences and provide accurate recommendations based on this information. Similar to what is claimed by previous literature (Puntoni et al., 2021), delighted respondents wrote that they had a positive experience with AI services due to that process. For example, one respondent claimed that Spotify knows her better than herself. Other respondents also praised (among other applications) streaming services because of the suggestions they can provide.

Positive affect. Besides the above elements connected to delightful AI interactions, we also extracted the emotional components of those interactions to identify the affective experience of delight. Similar to what has been found in the delight (Verma, 2003) and human–computer interaction (Shank et al., 2019) literature, delighted respondents reported positive emotions, ranging from low to high arousal (e.g., contentment and amazement).

In sum, considering both the appraisal of the elements and affective experience, our qualitative research identified nine elements of customer delight in AI service interactions. On these bases, we develop and validate a psychometrically sound multidimensional measurement scale. We conducted several studies to identify the structure of customer delight in the AI service interactions and to test their nomological relationships with related constructs. Table 2 provides an overview of the studies, detailing research methodology, sampling procedures, and sample characteristics for each study.

5.2. Studies 2a and 2b: Initial scale testing and refinement

Based on the literature review and qualitative study (Study 1), an initial pool of 134 items was administered in an online survey to a sample of 147 U.S. consumers in Study 2a, using seven-point agree/disagree questions (Table 2 details research methodology, sampling procedures, and sample characteristics). We first asked participants to recall and write down a delightful experience they had with a service powered by AI, and to fill out the questionnaire, keeping that delightful experience in mind. An exploratory factor analysis (EFA) revealed 95 items that had either low factor loadings (<0.40), or high cross-loadings (>0.25), or low communalities (<0.30) (Hair et al., 2006). Such items were deleted, and an EFA of the remaining 39 items yielded ten factors accounting for 78 % of the total variance. This study led to ten main themes in the final structure. Further data were collected online on U.S. consumers in Study 2b, yielding 195 usable questionnaires (see Table 2).

[1] In this phase, additional dimensions emerged, which were subsequently eliminated during the quantitative phases of the scale development process. To streamline the presentation, these dimensions are not discussed in detail here; however, further information is available upon request from the authors.

Table 2
Overview of studies 2–6.

Study aim	Research methodology	Sampling procedures and characteristics
Studies 2a-2b Item refinement	Data were collected through an online survey. A brief initial description introduced respondents to the questionnaire, then they were asked to recall and write down a delightful experience they had with a service powered by AI, and to answer the subsequent questions, having that experience in mind. The questionnaire used in Study 2a contained the initial set of 134 items. The questionnaire used in Study 2b contained 39 items (emerging from Study 2a). In both surveys, responses ranged between 1 = "strongly disagree" and 7 = "strongly agree" as end-points. Items were randomly mixed throughout the two surveys to enhance validity, and the surveys were broken into short sections. Demographic questions were asked at the end.	In Study 2a, U.S. adult consumers, recruited through Prolific, were asked to complete an online survey hosted by Qualtrics. In total, 150 surveys were collected in Study 2a, resulting in a 98 % usability ratio (questionnaires that passed the attention checks/ questionnaires collected). Thus, Study 2a included 147 responses (48.3 % females; average age of 36.57 years, SD = 13.42). KMO test for sampling adequacy = 0.87 (Kaiser and Rice 1974); power (calculated by G*power) = 99 %, medium effect size, 5 % alpha margin error. In Study 2b, 203 surveys were collected; 96 % usability ratio. Thus, Study 2b included 195 responses (49.7 % females; average age of 36.79 years, SD = 12.84). KMO test = 0.90 (Kaiser and Rice 1974); power (calculated by G*power) = 99 %, medium effect size, 5 % alpha margin error.
Study 3 Assessment of the scale dimensionality	Data were collected through an online survey. In the brief opening description of the study, respondents were asked to recall and write down a delightful experience they had with a service powered by AI, and to answer the subsequent questions referring to that experience. The survey included 30 items derived from Study 2b. The items were measured on 7-point scales anchored by 1 = "strongly disagree" and 7 = "strongly agree" as end-points, and the survey was broken into short sections. The survey also comprised two items measuring overall delight and demographic questions.	A distinctive U.S. sample of adult consumers was recruited through Prolific to complete an online survey hosted by Qualtrics. A total of 205 individuals participated in the survey; approximately 5 % were eliminated for failing the attention checks or for not providing an adequate description of the delightful experience with a service powered by AI requested at the beginning of the questionnaire. The total sample was composed of 195 respondents (power = 0.94; MacCallum and Hong 1997). Of these respondents, 40.5 % were females; average age of 39.81 years (SD = 14.22). Undergraduate or higher educated accounted for 59 % of the sample, followed by respondents with a high school education (37.4 %) or less (3.6 %).
Study 4 Assessment of scale validity through an MTMM analysis	Data were collected through an online survey. In the opening description, respondents were asked to recall and write down a delightful experience they had with a service powered by AI, and to answer the 30-item questionnaire referring to that experience. The items were measured on 7-point scales anchored by 1 = "strongly disagree" and 7 = "strongly agree" as end-points (method 1). To run an MTMM analysis, the same items were also measured using different anchors: 1 = "does not describe me at all" and 7 = "describes me completely" (method 2) (correlation between methods = 0.48, std. error = 0.03). Between the two sets of questions (i.e., method 1 and method 2), respondents performed activities unrelated to the topic under investigation to minimize the risk of simply remembering their responses to the items. The two sets of questions were presented in a randomized order and broken into short sections. Demographic questions were asked at the end.	A new U.S. sample composed of adult consumers was recruited through Prolific to complete an online survey hosted by Qualtrics. A total sample of 201 individuals participated in the survey and was used for the analyses (power = 0.95; MacCallum and Hong 1997). Of these, 48.8 % were female; average age of 39.13 years (SD = 13.85). Undergraduate or higher educated respondents accounted for 56.2 % of the sample, followed by respondents with a high school education (39.3 %) or less (4.5 %).
Study 5 Cross-country validity Study 6 Effects on consumer responses	The procedures for collecting new data to implement Study 5 and Study 6 are the same as those followed in Study 3. The survey was broken into short sections and consisted of the 30 items measured on 7-point scales (anchored by 1 = "strongly disagree" and 7 = "strongly agree"), the two items measuring the overall delight (2-item measure), the items measuring the dependent variables used for testing the predictive validity of the scale (i.e., intention to continue to use, positive WoM, tolerance to failure), and demographic questions.	A new U.K. sample of adult consumers was recruited through Prolific to complete an online survey hosted by Qualtrics. A total of 200 individuals participated in the survey; 6.5 % were eliminated for not providing an adequate description of the delightful experience with a service powered by AI requested at the beginning of the questionnaire. The final sample consisted of 187 respondents (power calculated by G*power = 98 %, medium effect size, 5 % alpha margin error); 51.3 % female, average age of 40.85 years (SD = 13.63). Undergraduate or higher educated accounted for 63.6 % of the sample, followed by respondents with a high school education (31 %) or less (5.4 %). This additional data collection was used to achieve two aims: in Study 5, to cross-country validate the scale by comparing this data with that collected in Study 4 in the U.S.; in Study 6, to test the predictive validity of the scale.

Note: All studies were conducted on different, independently collected samples. In all studies, several attention checks (e.g., "please, select the point 6") were used to identify participants who provided low-quality responses; we then excluded participants who failed these checks.

Items that contributed to lower factor-scale reliability were deleted, yielding 30 items, with three items for each factor, as our final scale. Ten factors emerged ($\chi^2(180) = 236.88$; $p < 0.01$) in the EFA, accounting for 76 % of the total variance. The Cronbach alphas of the ten dimensions ranged from 0.81 to 0.93.

5.3. Study 3: Assessment of scale validity

5.3.1. Scale dimensionality assessment

The pool of 30 items from Study 2b was then administered to a new sample of 195 U.S. consumers (Table 2 details research methodology, sampling procedures, and sample characteristics). A 10-factor confirmatory factor analysis (CFA) was run on the data using LISREL (Jöreskog and Sörbom, 2006). The model exhibited an excellent goodness-of-fit (Hu and Bentler, 1999): χ^2 (360) = 602.99; p = 0.00; CFI = 0.99; NNFI = 0.99; RMSEA = 0.05; SRMR = 0.04. Scale composite reliability always exceeded the cut-off level of 0.70, and average variance extracted (AVE) exceeded 0.50 for each factor (Hair et al., 2006). All standardized item-to-factor loadings were significant and strong, demonstrating adequate convergent validity. The shared variance between factors was less than the AVE for any pair, and the levels of the AVE for each construct are greater than the squared correlation involving the constructs (details are available in Supplementary Materials, Table I). These results show sound reliability and consistent structure for the 30-item scale.

Subsequently, a higher-order factor model was tested using a reflective model. A reflective instead of a formative model was used for two reasons: (a) the logic underlying reflective models better fits our syndromic conceptualization of customer delight in AI service interactions, as the ten main elements derived from the qualitative study are more appropriately considered to be manifestations of the latent construct of customer delight, rather than formative measures that define it; and (b) the coefficients in formative models can vary with the number and structure of the measures and factors used for the very same set of data (Bagozzi, 2007; 2011; Edwards, 2011; Howell et al., 2007), which makes them less appropriate in our context because of the ambiguity and instability resulting with formative models. We acknowledge that formative indicators have a place in marketing research where factors are functions of indicators. But in our case, indicators are functions of factors plus error. Reflective indicator models assume and test the implication that multiple indicators for each factor should converge and covary positively and do so relatively highly and uniformly, if they measure the same concept. One or more indicators from a set of indicators can be removed without changing the meaning of the factor in the reflective indicator approach. This is not true for formative indicators, where the meaning of a factor depends on each indicator, and indicators do not necessarily have to covary among themselves.

We introduced two second-order factors (i.e., *self-growth* and *functional elements*) and a third-order factor (i.e., customer delight in AI service interactions) to represent the ten specific first-order factors. We based this decision on two criteria: (a) the large amount of shared common variance between the first-order factors comprising the second-order and third-order factors, and (b) the semantic meaning shared by the first-order factors. The goodness-of-fit measures of the higher-order factor model were excellent: χ^2 (393) = 724.52; p = 0.00; CFI = 0.98; NNFI = 0.98; RMSEA = 0.06; SRMR = 0.06, demonstrating that the first-order factors can be represented more parsimoniously at a higher level of abstraction (details are available in Supplementary Materials, Figure II).

5.3.2. Measuring customer delight in AI service interactions as a single, unitary, abbreviated construct versus a multidimensional construct

In Study 3, we also collected and used two items (adapted from Finn 2005; $r = 0.82$) as indicators of a summary measure of overall customer delight. We tested the discriminant validity of our multidimensional construct and the abbreviated single-factor measure by estimating the disattenuated, latent variable correlations between multiple pairs of variables to test whether their 95 % confidence intervals fell significantly below 1.00 (Bagozzi and Yi, 2012). The overall abbreviated customer delight latent factor had positive disattenuated correlations (ranging from 0.61 to 0.85) with our ten first-order factors, yet were statistically below 1.00. The same result occurred with higher-order factors: namely, *self-growth elements* and *functional elements* showed disattenuated correlations of 0.05 and 0.50, respectively; the third-order factor of customer delight in AI service interactions showed a disattenuated correlation of 0.93 with overall abbreviated delight as a single factor (details are available in Supplementary Materials, Table II).

5.4. Study 4: multitrait-multimethod analysis testing construct validity

A new sample composed of 201 U.S. adult consumers was recruited in Study 4 (see Table 2 for details on research methodology, sampling procedures, and sample characteristics). A multitrait-multimethod (MTMM) matrix analysis was performed to provide a robust test for both convergent and discriminant validity of our measures (e.g., Bagozzi and Edwards 1998; Bagozzi 2011). The model of the MTMM matrix fit adequately: χ^2 (1604) = 3528.06, p = 0.00; CFI = 0.94; NNFI = 0.93; RMSEA = 0.07; SRMR = 0.06. This model was compared to the trait-only model ($\Delta\chi^2(\Delta df = 61) = 2259.09$, $p < 0.01$) and the method-only model ($\Delta\chi^2(\Delta df = 105) = 1517.36$, $p < 0.01$), showing significant improvements; therefore, we used the trait-method-error model to test construct validity. Trait variance was used to indicate the degree of convergent validity (Widaman 1985), and all factor loadings for traits proved to be statistically significant and high in magnitude (range: 0.64–0.93). Both random error variances and method variances ranged from low to moderate in magnitude. Overall, the systematic error due to the method is limited (3.9 % method 1; 4.6 % method 2), the average random error variance (24.5 %) and the average trait variance (67 %) are adequate (Williams et al., 1989). Thus, the convergent validity of the scale measures was demonstrated. Also, all traits achieved discriminant validity (all chi-square difference tests were higher than 119.29, $p < 0.05$). Details are available in Supplementary Materials, Table III.

5.5. Study 5: Cross-country validation of the scale

As further evidence for validity (e.g., Van Auken et al., 2006; Grappi et al., 2018; Zawadzka et al., 2021), Study 5 tested the cross-country applicability of the measurement scale. We collected data in the U.K. to compare with that obtained in the U.S. (Study 4). The selection of these two countries was based on the following considerations. First, both are highly developed, English-speaking nations, yet they exhibit cultural differences (e.g., they differ in future orientation as Americans focus more on immediate gains, while in the U.K., individuals tend to integrate longer-term considerations; Hofstede, 2001) and notable differences in their AI capacity. Both countries rank highly on the Global AI Index, which evaluates countries based on AI implementation, innovation, and investment (Tortoise Media, 2024). The U.S. ranks first, while the U.K. ranks fourth. Notably, the U.S. scores exceptionally high on the two primary dimensions of the index: the first capturing a country's absolute AI capacity on the global stage and the second measuring AI capacity relative to population or economic size. In contrast, the U.K.'s scores in both dimensions are significantly lower, approximately half of those of the U.S. These differences make the U.K. a particularly valuable setting for cross-country validation, offering a meaningful context in which to examine the generalizability of the scale. The additional sample used for this purpose consisted of 187 U.K. respondents. Details on research methodology, sampling procedures, and sample characteristics are presented in Table 2.

First, we conducted a CFA on the 30-item scale collected in the U.K. (χ^2 (360) = 614.70; p = 0.00; CFI = 0.97; NNFI = 0.97; RMSEA = 0.06; SRMR = 0.05) and tested the higher-order factor model (χ^2 (393) = 747.98; p = 0.00; CFI = 0.96; NNFI = 0.96; RMSEA = 0.07; SRMR =

0.08). Next, we formally compared the data collected in the U.S. (Study 4) and in the U.K through a two-group analysis. To verify whether the scale and its conceptualization hold across groups, it is necessary to proceed with progressive and sequential tests of equivalence (i.e., generalizability) (Byrne 1998; Bollen 1989; Cheung and Rensvold 1999). Configural equivalence for the 30-item scale was established, as an excellent group-model fit was obtained (χ^2 (786) = 1525.31; p = 0.00; CFI = 0.96; NNFI = 0.96; RMSEA = 0.06; SRMR = 0.08). To test for metric equivalence, we first constrained all factor loadings of the ten first-order factors to be equal across countries (model fit: χ^2 (806) = 1552.12; p = 0.00; CFI = 0.96; NNFI = 0.96; RMSEA = 0.07; SRMR = 0.08). A χ^2 difference test between this model and the configural equivalence model was nonsignificant ($\Delta\chi^2(20) = 26.81$, $p > 0.10$), supporting the first-level metric equivalence of the scale. Then, we ran a further model constraining all factor loadings and the links between the latent variables to be equal across countries; this model yielded a satisfactory fit (χ^2 (816) = 1556.59; p = 0.00; CFI = 0.96; NNFI = 0.96; RMSEA = 0.07; SRMR = 0.08). The χ^2 difference test comparing the two models was nonsignificant ($\Delta\chi^2(10) = 4.47$, $p > 0.10$), supporting the full metric equivalence of the delight customer in AI service interactions scale. Thus, the model proposed generalizes across the U.K. and the U.S. (details are available in Supplementary Materials, Table IV).

5.6. Study 6: assessment of predictive validity and customer response strategies

The same 187 U.K. participants used in Study 5 are used to assess the scale's predictive validity. Respondents answered the 30-item scale and the measures of three relevant customer responses: intentions to continue to use the service powered by AI (adapted from McLean and Osei-Frimpong 2019; Venkatesh et al., 2012), intentions to spread positive WoM (adapted from Amatulli et al., 2021), and tolerance to failure (adapted from Collier et al., 2018). We tested the comparative predictive power of the overall abbreviated customer delight factor versus our customer delight in AI service interactions higher-order factor. Overall abbreviated customer delight as a summary single factor significantly predicts intention to continue to use the service powered by AI (std. coefficient = 0.63, $p < 0.01$, $R^2 = 0.40$), positive WoM (std. coefficient = 0.68, $p < 0.01$, $R^2 = 0.47$), and tolerance to failure (std. coefficient = 0.40, $p < 0.01$, $R^2 = 0.16$). The higher-order customer delight in AI service interactions also significantly predicts the three dependent variables, but at consistently higher levels than for summary overall customer delight[2] (intention to continue to use the service powered by AI: std. coefficient = 0.70, $p < 0.01$, $R^2 = 0.48$; positive WoM: std. coefficient = 0.75, $p < 0.01$, $R^2 = 0.56$; tolerance to failure: std. coefficient = 0.47, $p < 0.01$, $R^2 = 0.22$). Findings showed that our multidimensional measure adds predictive value, as well as greater diagnostic and evaluative detail, over a simple summated, single-factor measure (details are available in Supplementary Materials, Table V).

5.7. Discussion

Fig. 1 details the structure and dimensions of customer delight in the AI service interactions that emerged from the scale development process, along with the designation of items measuring each dimension. Customer delight in AI service interactions reflects a customer's intense positive emotional response (i.e., positive affect) associated with a set of eight appraised positive elements of the interactions with AI services.

The remarkable capabilities demonstrated by the technologies embedded in AI services are the basis for the positive elements appraised by customers in their interactions with the services. Mechanical, thinking, and feeling AIs manifest in specific capabilities able to generate relevant experiences. Therefore, AI services' capabilities contribute to positive interactions with customers and consequently to positive customer experiences. The combination of the eight elements illustrated above with positive affective reactions reflects a delightful experience with AI services. In summary, this comprehensive syndromic perspective for customer delight in AI service interactions better recognizes the complexity and peculiarities of customer appraisals of service encounters in the specific context of AI. Moreover, our structure acknowledges that delightful customer experiences are an aggregation of multiple elements that can hold more or less importance depending on specific AI services involved.

Specifically, based on Huang and Rust (2021; 2024), we can expect that while mechanical and thinking AIs manifest in capabilities able to make customers experience delight mainly based on *ease of use*, *functional*, or *human-like relationships* elements, feeling AI, adding feeling capabilities, will be able to better provide delightful experiences based on *self-growth elements*. With the following study, we aim to test this prediction by comparing the structure of customer delight in AI service interactions across the three levels of AI and related capabilities.

6. Applying our measure on different AI service interactions (study 7)

Study 7 aims to answer the second objective of the research, that is, to test the ability of our measure to acknowledge the variation in customer delight depending on different AI service interactions. A between-subjects experiment was implemented to assess the structure of customer delight in AI service interactions between different services powered by AI and to reveal commonalities and differences.

6.1. Procedures and participants

We selected three AI services representing the three levels of AI identified by the Huang and Rust (2021) framework: mechanical, thinking, and feeling. The primary advantages of mechanical AI are standardization and automation; thus, we selected basic chatbots (CB) as representatives of the first level of the framework. The primary advantage of thinking AI is personalization, and for this reason, we selected recommendation systems (RS) as representatives of the second level of the framework. Finally, the primary advantage of feeling AI is relationalization (i.e., personalized relationships; Huang and Rust, 2017; 2018). This level is characterized by two different types of AI: low-end feeling AI, which mainly deals with basic customer service, and high-end feeling AI, characterized by greater abilities to understand in a customer care setting (Huang and Rust, 2021). Low-end feeling AI is already present in the current technological landscape and widely available to the public (e.g., virtual conversational agents such as Alexa or Siri), whereas high-end feeling AI is still emerging and not widely known by the mass market (Huang and Rust, 2024; Liu-Thompkins et al., 2022). For this reason, to ensure adequate reliability of the results, we selected low-end feeling services powered by AI as representatives of the

[2] Note that because we are making comparisons between models with the same dependent variables, it is appropriate to compare these raw statistics with each other (Batra et al., 2012).

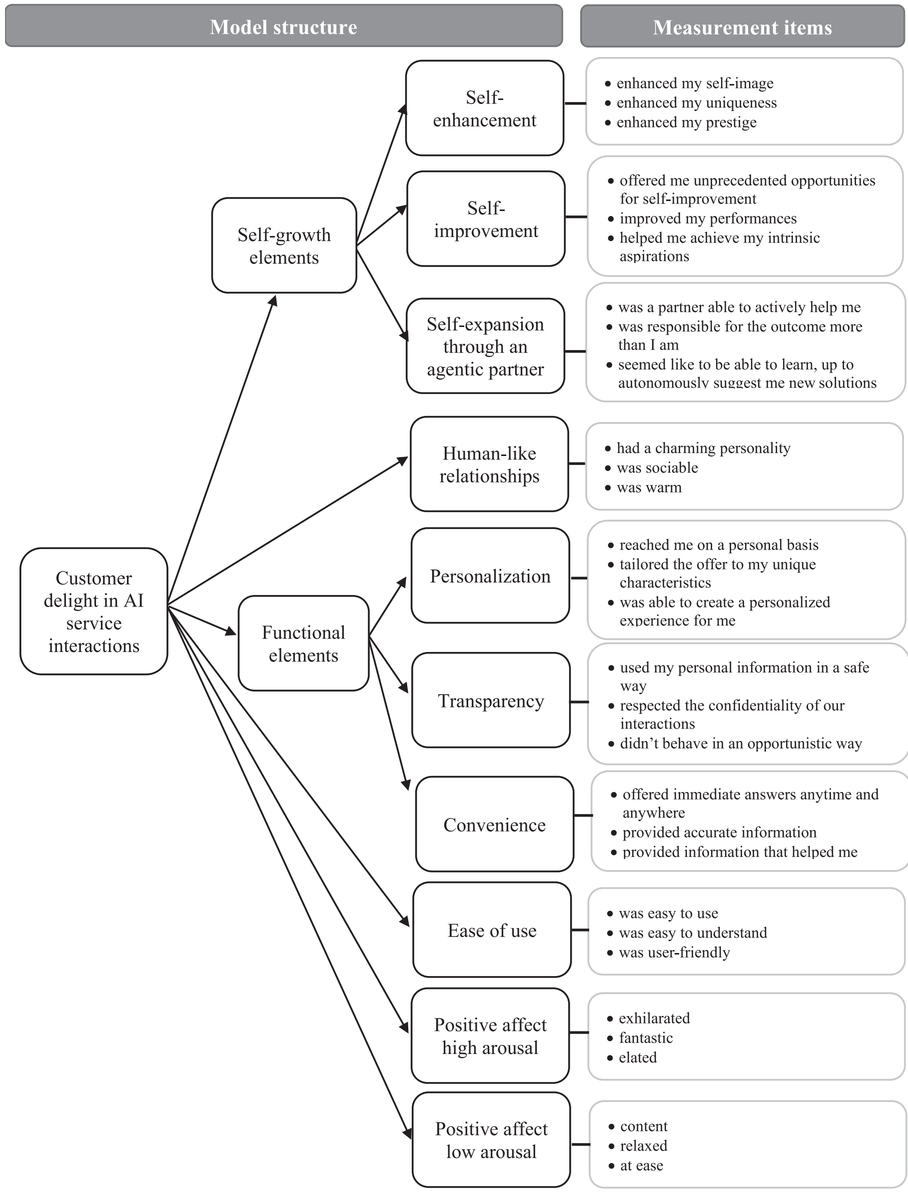

Fig. 1. Customer delight in AI service interactions: model structure and measurement items (study 1–study 6).

third level, that is, virtual conversational agents (VCA).[3]

Each respondent was asked to describe a delightful experience with one of the services powered by AI (i.e., basic CB, RS, or VCA) randomly assigned and then answer the items of the customer delight in AI service interactions scale with that experience in mind. Demographic questions were also collected. U.K. samples composed of adult consumers were recruited through Prolific to complete online surveys hosted by Qualtrics. We selected respondents who own and have used the specific AI-based service they are asked to refer to by using (1) Prolific tools for selecting respondents when available and (2) a few opening questions in the questionnaire. This ensured respondents who use these specific services were reached. A total of 667 individuals participated in the survey. Approximately 13 % were eliminated for failing attention checks, not using the service, or not providing an adequate description of a delightful experience with an AI-powered service, as requested at the beginning of the questionnaire. The final sample was comprised of 581 respondents (195 in the basic CB condition, 190 in the RS condition, and 196 in the VCA condition). Of these, 51.8 % were female, average age of 39.54 years (SD = 12.37). Undergraduate or higher educated respondents accounted for 62 % of the sample, followed by respondents with a high school education (34.9 %) or less (3.1 %). The experimental groups did not vary in gender ($\chi^2(4) = 1.68$; $p = 0.80$), age ($F(2, 578) = 2.23$; $p = 0.11$), or educational level ($\chi^2(8) = 7.65$; $p = 0.47$).

[3] To assess whether the three selected examples were accurately identified as representative of the three categories in the Huang and Rust (2021) framework, a validation test was conducted. Participants were randomly assigned to one of three AI descriptions (mechanical AI, thinking AI, or feeling AI) and, after reading the assigned description, they were asked to indicate which of the three examples of service AI (CB, RS, or VCA) best corresponded to the description they received. The sample consisted of 120 U.K. respondents (50.8% female; *M* age = 45.93, *SD* = 12.46) randomly assigned to the three scenarios. When presented with the mechanical AI description, most respondents (36 out of 40) selected CB as the better-fitting example; when presented with the thinking AI description, the majority (36 out of 41) selected RS as the better-fitting example; when presented with the feeling AI description, the majority (32 out of 39) selected VCA. The chi-square test conducted on these data was significant, χ^2 (4, N = 120) = 155.47, $p < 0.001$. Thus, findings confirmed that participants recognized the intended categories and correctly classified the examples employed in this study.

6.2. Results

We first analyzed the structure of customer delight in AI service interactions separately for each of the services powered by AI. For VCA (χ^2 (393) = 809.27; p = 0.00; CFI = 0.97; NNFI = 0.96; RMSEA = 0.07; SRMR = 0.08), RS (χ^2 (393) = 799.68; p = 0.00; CFI = 0.96; NNFI = 0.95; RMSEA = 0.07; SRMR = 0.09), and basic CB (χ^2 (393) = 903.51; p = 0.00; CFI = 0.97; NNFI = 0.96; RMSEA = 0.08; SRMR = 0.09) the models showed satisfactory fits, and all factor loadings were substantial and significant. Next, we compared the measurement model for the data collected in the three groups. Configural equivalence for the 30-item scale was established, as an acceptable group-model fit was obtained (χ^2 (1179) = 2512.94; p = 0.00; CFI = 0.96; NNFI = 0.96; RMSEA = 0.08; SRMR = 0.09). The test for the full metric equivalence in which all

Table 3
Assessment of the customer delight structure comparing different AI services (study 7).

Third-order factor	Std. loading (t-value)	Second-order factor	Std. loading (t-value)	First-order factor	Std. loading (t-value)
Customer delight in AI service interactions	CB, RS = 0.81*** (11.08) VCA = 0.96*** (10.10)	**Self-growth elements**	CB, RS, VCA = 0.58 (–-)	**Self-enhancement**	
				enhanced my self-image	CB, RS, VCA = 0.91 (–-)
				enhanced my uniqueness	CB, RS, VCA = 0.94*** (39.13)
				enhanced my prestige	CB, RS, VCA = 0.91*** (36.37)
			CB, RS, VCA = 0.65*** (10.77)	**Self-improvement**	
				offered me unprecedented opportunities for self-improvement	CB, RS, VCA = 0.88 (–-)
				improved my performances	CB, RS, VCA = 0.90*** (29.46)
				helped me achieve my intrinsic aspirations	CB, RS, VCA = 0.89*** (29.00)
			CB, RS, VCA = 0.94*** (11.23)	**Self-expansion through an agentic partner**	
				was a partner able to actively help me	CB, RS, VCA = 0.71 (–-)
				was responsible for the outcome more than I am	CB, RS, VCA = 0.69*** (14.38)
				seemed like to be able to learn, up to autonomously suggest me new solutions	CB, RS, VCA = 0.73*** (15.12)
	CB, RS, VCA = 0.99*** (13.75)	**Functional elements**	CB, RS, VCA = 0.69 (–-)	**Convenience**	
				offered immediate answers anytime and anywhere	CB, RS, VCA = 0.66 (–-)
				provided accurate information	CB, RS = 0.83*** (14.59); VCA = 0.98*** (13.89)
				provided information that helped me	CB, RS = 0.80*** (14.60); VCA = 0.92*** (12.76)
			CB, RS, VCA = 0.64*** (10.86)	**Transparency**	
				used my personal information in a safe way	CB, RS, VCA = 0.85 (–-)
				respected the confidentiality of our interactions	CB, RS, VCA = 0.94*** (25.70)
				didn't behave in an opportunistic way	CB, VCA = 0.51*** (12.53); RS = 0.70*** (8.90)
			CB, RS = 0.72*** (10.85) VCA = 0.85*** (10.01)	**Personalization**	
				reached me on a personal basis	CB, RS, VCA = 0.80 (–-)
				tailored the offer to my unique characteristics	CB, RS, VCA = 0.90*** (26.20)
				was able to create a personalized experience for me	CB, RS, VCA = 0.94*** (26.91)
	CB, RS, VCA = 0.56*** (13.29)			**Human-like relationships**	
				had a charming personality	CB, RS, VCA = 0.89 (–-)
				was sociable	CB, RS, VCA = 0.96*** (37.99)
				was warm	CB, RS, VCA = 0.92*** (34.77)
	CB = 0.78*** (12.70) RS, VCA = 0.61*** (11.90)			**Ease of use**	
				was easy to use	CB, RS, VCA = 0.89 (–-)
				was easy to understand	CB, RS, VCA = 0.87*** (33.08)
				was user-friendly	CB, RS, VCA = 0.90*** (31.42)
	CB, RS, VCA = 0.66*** (15.24)			**Positive affect-high arousal**	
				exhilarated	CB, RS, VCA = 0.87 (–-)
				fantastic	CB, VCA = 0.93*** (24.81); RS = 0.71*** (13.37)
				elated	CB, RS, VCA = 0.87*** (26.36)
	CB, RS, VCA = 0.63*** (13.33)			**Positive affect-low arousal**	
				content	CB, RS, VCA = 0.70 (–-)
				relaxed	CB, RS, VCA = 0.92*** (20.79)
				at ease	CB, RS, VCA = 0.94*** (20.96)

*** If $p < 0.001$. CB: basic chatbots; RS: recommendation systems; VCA: virtual conversational agents. N = 581 respondents (195 in CB condition, 190 in RS condition, 196 in VCA condition).

the loadings were constrained to be equal across groups was not supported, as the χ^2 difference test between the configural and the full metric equivalence models was significant ($\Delta\chi 2(40) = 66.69$, $p < 0.05$). Instead, the test for partial metric equivalence yielded a satisfactory fit for the model in which all the loadings were constrained to be equal across groups, except for four loadings (see Table 3) (χ^2 (1215) = 2554.14; p = 0.00; CFI = 0.96; NNFI = 0.96; RMSEA = 0.08; SRMR = 0.09). A χ^2 difference test between the configural and the partial metric equivalence models was nonsignificant ($\Delta\chi 2(36) = 41.20$, $p > 0.05$), thus supporting the partial metric equivalence of the scale. Then, we ran further models progressively constraining the links between the latent first- and second-order variables to be equal across groups; the model that proved to be superior is the one detailed in Table 3. The fit of the model was satisfactory (χ^2 (1232) = 2581.25; p = 0.00; CFI = 0.96; NNFI = 0.96; RMSEA = 0.08; SRMR = 0.09). A χ^2 difference test between the partial metric equivalence model and this model was nonsignificant ($\Delta\chi 2(17) = 27.11$, $p > 0.05$), therefore supporting the model imposing the additional constraints. Thus, the model generalizes across the three different services powered by AI. This provides additional evidence for the validity of the new scale.

6.3. Discussion

Results show the dimensions that played the same role in the three contexts, that is, *functional elements*, *positive affect-high arousal*, *positive affect-low arousal*, and *human-like relationships*. They are the common

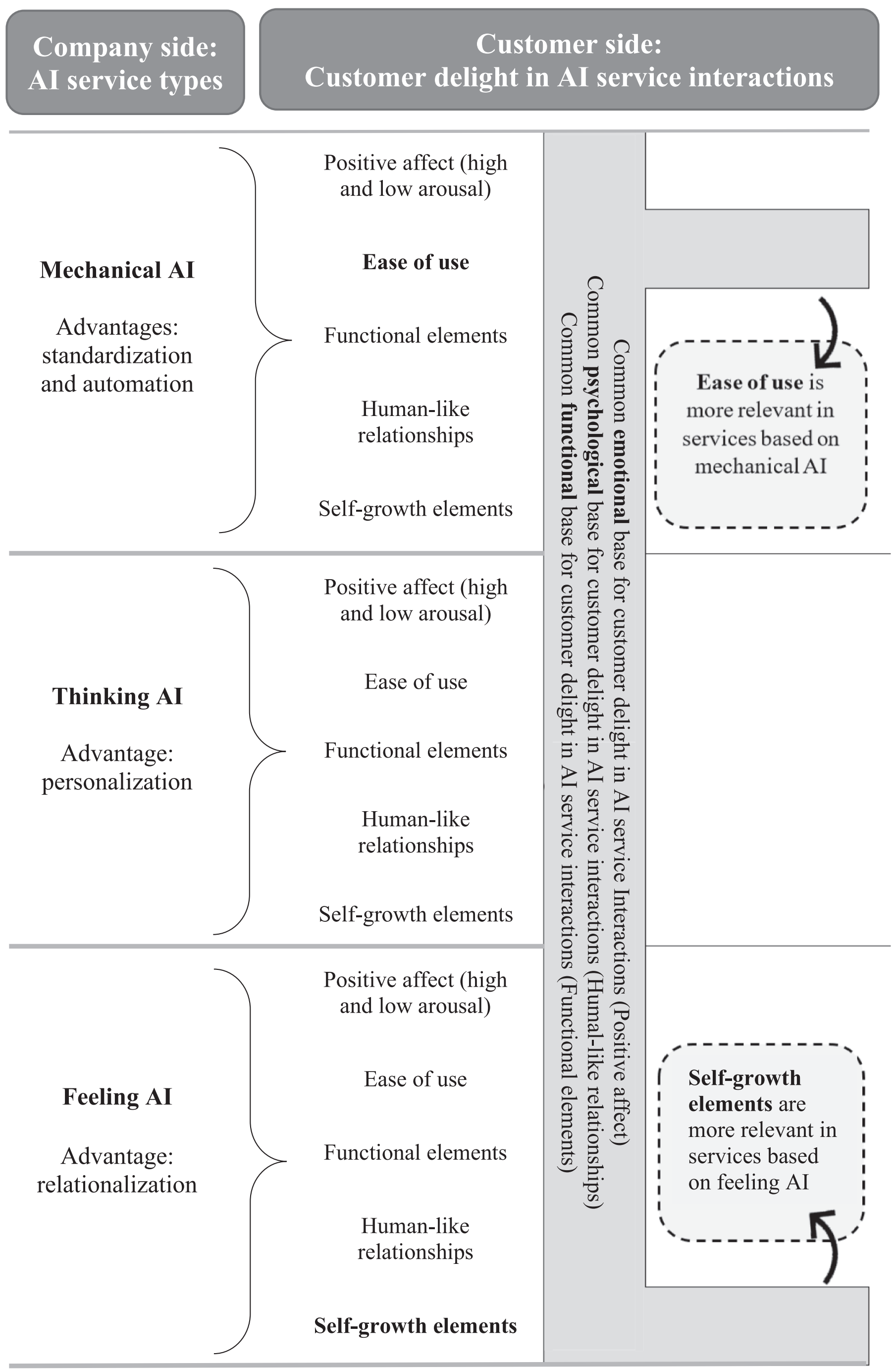

Fig. 2. Comparing mechanical, thinking, and feeling AI: graphical representation of results (study 7).

base for customer delight in AI service interactions in all three types of AI services. The two dimensions of *ease of use* and *self-growth elements* showed instead to differ between the groups. Customer delight reflects the *ease of use* element to a greater extent in basic CB compared to the other two groups (RS and VCA). This result is aligned with previous research acknowledging the relevance of clarity and easy-to-understand aspects of mechanical AI, as often customers interact with this type of AI in specific situations of time constraints (Juquelier et al., 2025; Ostrom et al., 2021) or to delegate the performance of manual and mechanical tasks such as cooking or cleaning the home (De Bellis and Johar, 2020; Puntoni et al., 2021). In line with our prediction, *self-growth elements* proved to be more relevant for VCA compared to the other two groups (basic CB and RS). Results explicated a distinctive path to customer delight in feeling AI service interactions, where the *self-growth elements* play a central role. Fig. 2 graphically depicts the results.

Compared to other AI services, those with feeling capabilities are critical for creating and maintaining personalized interactions with the customer (Choi et al., 2021; Huang and Rust, 2021). In these interactions, customers can not only feel enabled by the capabilities of the AI services to pursue goals and tasks, but also feel a direct link between the AI services and their desired self-state, that is, the kind of person they desire to be (i.e., *self-growth elements*). This evidence can also be traced back to research on branding, specifically on strong attachment to brands (Park et al., 2013) and the idea of brands as able to offer several resources to help consumers achieve desired goals (Reimann and Aron, 2009; Richins, 1994; Kleine et al., 1989).

7. General discussion

7.1. Theoretical contribution

Delight is an essential construct in the service literature (Oliver et al., 1997) due to the positive managerial effects that this emotional state can have in different contexts (e.g., Finn, 2005). Recent work has proposed a new and holistic conceptualization of delight that also takes into account the appraisal of the elements that are part of the service and that contribute to a delightful experience (Parasuraman et al., 2021). As AI has specific and "magical" features that can lead consumers to have peculiar experiences (Puntoni et al., 2021; Tully et al., 2025), we applied this holistic approach to capture the unique elements that constitute a delightful experience in AI service interactions. With seven studies, this work proposes a new conceptualization of customer delight in AI service contexts and explores the positive effects of customer delight and how it changes in different AI contexts.

This research contributes to AI service literature (e.g., Bagozzi et al., 2022; Blut et al., 2024) and customer delight literature (Barnes and Krallman, 2019) in several ways. Although managerial and scientific research have emphasized the relevance of delighting customers (e.g., Bisht et al., 2024; Oliver et al., 1997), research so far has focused the lens of customer delight in traditional service contexts, neglecting service AI interactions. Filling this gap, and through a syndromic approach (Averill, 1980), we enrich AI service literature and customer delight literature by proposing a new structure (and measure) that explains what it means to delight customers in AI service interaction contexts (Studies 1–6). According to our results, customer delight is not only composed of affective elements, but also of the appraisal of several delightful elements peculiarly connected to the AI service interaction context (e.g., *ease of use*, *self-improvement*). This approach corroborates previous literature that emphasizes the peculiar and extended range of experiences that customers can have in AI contexts (Puntoni et al., 2021). Indeed, the results of our work show that a delightful AI service interaction experience is composed of several elements that can deal with utilitarian, relational, and identity aspects connected with the customer experience of AI interactions (e.g., Pitardi and Marriott, 2021). Furthermore, our research also confirms previous findings that explore the positive effects of customer delight on several relevant outcomes (e.g., WoM; Chitturi et al., 2008), showing how this positive influence of customer delight is also present in the AI service interaction realm.

Our research also contributes to the AI intelligence theory proposed by Huang and Rust (2018; 2021; 2022; 2024). According to this approach, the AI realm is heterogeneous and made up of different types of intelligences (mechanical, thinking, and feeling) that contribute to different types of service functions and customer benefits. Previous literature has applied this framework to explore how different types of AI can lead to different effects (e.g., Choi et al., 2021; Larivière et al., 2024; Schepers et al., 2022). Our research corroborated this approach and found that the customer delight structure changes according to the different type of AI, with elements that are equally relevant across conditions and with others that are more relevant for a particular type of AI: specifically, in the case of mechanical AIs, *ease of use* is an element particularly relevant; at the same time, *self-growth elements* are particularly relevant for feeling AIs (Study 7).

7.2. Managerial implications

This study also offers valuable insights for practitioners by conceptualizing customer delight in AI service interactions, identifying its elements, and developing a tool able to measure its validity and reliability. First, the scale can serve as a roadmap for managers to guide them in identifying the attributes of their AI services that enable building customer delight (i.e., customer delight elements). Therefore, managers who want to delight their customers should design the AI services based on the elements of customer delight in AI service interactions. Take the *self-growth element* and its three components: *self-enhancement* (e.g., enhancing user uniqueness), *self-improvement* (e.g., facilitating self-improvement), and *self-expansion through an agentic partner* (e.g., offering suggestions and useful outcomes). Managers could use the nine items measuring these components to get inspiration about the characteristics their AI service should have. More specifically, managers could use the items to create and program the tasks that the AI should perform, as well as the modality with which these tasks should be performed when interacting with customers. Some leading companies in the AI service sector are already incorporating aspects of self-growth into the design of their AI services. One of them is Amazon, which has programmed its voice assistant, Alexa, to be a helper and assistant to users, making their lives "more meaningful" (Amazon, n.d.). Anecdotal evidence of the success of this practice is represented by the fact that users emphasized self-growth aspects in their reviews, such as making a good impression with a vegan friend thanks to Alexa's recommendation about a recipe (i.e., *self-enhancement*) or the enhancement and improvement of the life of vulnerable consumers (i.e., *self-improvement*).[4] Another example of success in self-improvement for vulnerable customers is the app Tallk that Samsung has developed to enable people with ALS to communicate and interact with their surroundings using Samsung Voice Assistant (Samsung, 2020).

Regarding the second element of our scale, *human-like relationships*, managers should focus on making AI more charming, sociable, and warm. Companies could follow the example of Virgin Voyages, which has made a significant investment to enable its chatbot, Vivi, to provide more human-like responses (Drenik, 2023).

Concerning the *functional elements* and their three components *personalization* (e.g., creation of personalized experience for the user), *transparency* (e.g., respect of the confidentiality of interactions with the user), and *convenience* (e.g., providing immediate answers anytime and anywhere to the user), managers could use the nine items here to get inspiration about how to design the AI service to provide users with an interaction intrinsically characterized by personalization, transparency, and convenience. One way could be designing services whose offerings are based on the customer's unique characteristics, made by privacy

[4] URLs to the online reviews available upon request.

policies, and delivered to the customer efficiently and promptly. An example of personalization and convenience is Spotify. Its recommendation system, indeed, can create personalized daily playlists based on users' listening habits throughout the day and match the music to the user's current mood and needs (Spotify, 2023). An example of transparency is Apple, with its general privacy policy and specifically for Siri, its voice assistant. On its website, Apple reports that "Siri is designed to protect your information and enable you to choose what you share", clearly promoting and declaring its privacy-by-design approach (Apple, 2025).

Regarding the *ease of use element*, managers should focus on designing AI services that are easy to use, easy to understand, and user-friendly. A successful case is iRobot Roomba. The company emphasizes explicitly its ease of use as all consumers must do is "just tell" the device where to clean through its app (iRobot, 2019), and customers agree mentioning the fact that it is "easy to clean" and "easy to use" in the reviews they publish online.[5]

Concerning the last two elements of our scale, namely *positive affect high arousal* and *positive affect low arousal*, managers should prioritize the implementation of features that enhance the AI service's ability to make the user feel exhilarated, fantastic, elated, content, relaxed, and at ease.

In summary, regardless of the specific element, our scale can help companies that are already implementing one or more elements in the design of their AI service, such as Amazon, Spotify, and Apple, measure the impact of their actions and return on investment in terms of customer delight. Moreover, it can help other companies that have not yet implemented any of the elements to have a clearer idea and roadmap to follow, thereby maximizing the success of their future investments aimed at increasing customer delight.

Second, our research indicates that customer delight has a positive impact on key marketing outcomes. Therefore, by enhancing the aspects of their AI service related to the elements we identified, managers can not only elicit customer delight but also improve performance on key marketing objectives, namely intention to use the AI service again, positive WoM, and tolerance to failure, avoiding or mitigating negative customer reactions that can harm their business and reputation, such as negative WoM and a high churn rate (Schwartz, 2023).

Third, we examined the elements of customer delight in AI service interactions and their relevance at three different levels of AI (mechanical AI, thinking AI, and feeling AI; Huang and Rust, 2021). All the elements that contributed to the final structure of customer delight in AI service interactions were found to be important, even though their relevance may vary based on the type of AI service and its associated advantages. This has practical implications for managers in prioritizing the elements of delight that need to be implemented or improved for a specific AI service. Indeed, based on our results, *functional* and *human-like relationships elements* serve as a sort of baseline for customer delight in AI service interactions, as they are similarly relevant across all three levels of AI. Therefore, all the brands that provide AI services should consider implementing or improving the two elements to make a first step toward customer delight. However, our results also suggest that companies implementing mechanical AI in their services need to focus, in particular, on *ease of use*. On the other hand, companies using feeling AI for their services need to put particular emphasis on the *self-growth element*.

In conclusion, by focusing on the elements connected to customer delight, the concrete measures we derived, and the specificities that emerged for the different types of AI services, managers can concretely produce delightful experiences in AI service interactions that satisfy customer needs and outperform the competition.

[5] URLs to the online reviews available upon request.

7.3. Limitations and further research

Our study offers valuable insights addressing customer delight in AI service interactions; however, it is also important to acknowledge its limitations, which in turn present opportunities for future research. The rigorous scale development process employed in this study ensures both the generalizability and validity of the measures, further supported by the evidence related to associated customer responses. Nonetheless, future research should consider additional customer responses to delight (e.g., willingness to purchase services at a premium price) to further broaden and deepen our understanding of how customer delight enhances value creation in AI-driven service companies. Moreover, we recommend incorporating actual behavioral data (e.g., customer demonstrated tolerance to service failures, such as the decision to remain with a service provider despite encountering problems) to address an additional limitation of the present study, that is, its reliance on self-reported measures.

Additionally, it is worth noting that this study considered various existing AI software/platforms to develop a reliable measurement scale of customer delight in AI service interactions. Future studies should focus on specific AI service applications (e.g., service robots, service AI chatbots) to advance the understanding of consumer responses in the service industry. Also, although we had a more specific approach in Study 7, future studies should focus on specific types of service powered by AI (e.g., frontline service robots; Pozharliev et al., 2021) to highlight possible idiosyncratic consumer reactions. We also suggest that additional studies could apply a longitudinal analysis to discover how customer delight evolves, thereby gaining new and useful insights.

Moreover, it is worth noting that, although our findings imply that customer delight affects important customer responses, our results do not imply that this element is the only driver of such reactions. Consumer individual characteristics (e.g., materialism, Bagozzi et al., 2020; social identity, need for stimulations/need for cognition, Cacioppo and Petty, 1982; loneliness, Shrum et al., 2023) could also play a role in influencing such outcomes by either bolstering or suppressing customer delight effects.

Furthermore, although we validated the scale in developed Western countries, we acknowledge the importance of further validation with other countries (e.g., Asian, African, and South American countries) to examine the stability and validity of the customer delight scale across different countries.

Lastly, but most importantly, this work is based on the current state of the art of technology and AI. New technologies are emerging in the market that might challenge the delight structure presented in this work. For example, the type of AI that can emotionally connect with users is spreading, shifting the frontiers of high-end feeling AI (Huang and Rust, 2022; 2024). Future research can further investigate the structure of delight with those evolving types of technologies. We claim and suggest that this process can be studied through what is called a living syndrome, where the elements and organization of delight might change as research knowledge and customer experiences evolve. This means that the structure of the syndrome proposed in this study may evolve into a new and updated one, encompassing new types of emotional experience, as well as the appraisal of additional elements not considered in this study.

Ethical approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. The identity of respondents was completely anonymous. Informed consent was obtained from all individual participants included in the study. The Ethics Committee of the Luiss Guido Carli University (Italy) approved the research program on May 5, 2023.

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CRediT authorship contribution statement

Silvia Grappi: Writing – original draft, Supervision, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization, Writing – review & editing. **Simona Romani:** Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization, Writing – review & editing. **Luigi Monsurrò:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization, Writing – review & editing. **Ilaria Querci:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization, Writing – review & editing. **Richard P. Bagozzi:** Supervision, Methodology, Formal analysis, Data curation, Conceptualization, Writing – review & editing.

Declaration of competing interest

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

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbusres.2025.115808.

Data availability

Data will be made available on request.

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