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# How Trust in Human-like AI-based Service on Social Media Will Influence Customer Engagement: Exploratory Research to Develop the Scale of Trust in Human-like AI-based Service

Jin Jingchuan
*PhD Candidate, Department of Business Administration, Kyung Hee University, Seoul, Korea*, jinjc90@khu.ac.kr

Shali Wu
*Adjunct Professor, Department of Business Administration, Kyung Hee University, Seoul, Korea*, Shali.wu@khu.ac.kr



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# How Trust in Human-like AI-based Service on Social Media Will Influence Customer Engagement: Exploratory Research to Develop the Scale of Trust in Human-like AI-based Service☆

Jin Jingchuan [a,*], Shali Wu [b]

[a] PhD Candidate, Department of Business Administration, Kyung Hee University, Seoul, Korea
[b] Adjunct Professor, Department of Business Administration, Kyung Hee University, Seoul, Korea

**Abstract**

**This research is on how people's trust in human-like AI-based service will influence customer engagement (CE). This study will discuss the relationship between trust and CE and explore how people's trust in AI affects CE when they lack knowledge of the company/brand. Items from the philosophical study of trust were extracted to build a scale suitable for trust in AI. The scale's reliability was ensured, and six components of trust in AI were merged into three dimensions: trust based on Quality Assurance, Risk-taking, and Corporate Social Responsibility. Trust based on quality assurance and risk-taking is verified to positively impact customer engagement, and the feelings about AI-based service fully mediate between all three dimensions of trust in AI and CE. The new trust scale for human-like AI-based services on social media sheds light on further research. The relationship between trust in AI and CE provides a theoretical basis for subsequent research.**

*Keywords:* Customer engagement, Artificial intelligence, Trust in AI, Service, Social media

## 1. Introduction

Sora, an artificial intelligence model that can generate videos from text descriptions, was released by OpenAI in early 2024. Moreover, half a year ago, Microsoft released an AI companion, Copilot, on the Windows system. These facts not only make people aware of the explosive development of AI technology but also mean that AI technology has gradually penetrated people's daily lives as a convenient tool and easier-to-use service. However, people are not ready to welcome AI into their daily lives. Especially on the issue of trust in AI, even though many researchers and scholars have discussed it at the theoretical level (Glikson and Woolley 2020; Ryan 2020; Siau and Wang 2018), the reality is that many ordinary people are unaware of them. Before AI fully enters public life, a trust scale more suitable for AI technology is essential, especially for human-like AI, to help us better understand how ordinary people trust AI.

Over the past two decades, customer engagement (CE) has received considerable attention from marketing researchers and managers (Harmeling et al. 2017; Kumar et al. 2010; Lim et al. 2022). As this research topic became widespread, many different perspectives and findings emerged. One of the debates is the influence between trust and CE. Some studies argue that trust should be an antecedent for CE (Jaakkola and Alexander 2014; Van Doorn et al. 2010; Youssef et al. 2018), while some other studies emphasize that trust should be viewed as a consequence of CE (Brodie et al. 2013; So et al. 2016b; Vivek, Beatty, and Morgan 2012). This study will focus on how trust in human-like AI-based service will enhance customer engagement and whether feelings about AI will mediate between trust and customer engagement,

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* Corresponding author.
E-mail addresses: jinjc90@khu.ac.kr (J. Jingchuan), Shali.wu@khu.ac.kr (S. Wu).

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especially when people lack understanding of the company/brand.

Emotion is the projection/display of a feeling and is treated as a mediator between trust and CE (Pansari and Kumar 2017; Shouse 2005). However, some research indicates that emotion does not mediate between trust and CE (de Oliveira Santini et al. 2020). To better understand how people's trust in AI affects CE, feelings about AI are adopted to replace emotions. Unlike emotion, feelings are sentiments based more on past experiences and knowledge. This study will limit people's understanding of companies/brands to verify whether feelings about AI can play a mediating role. It can effectively prevent the influence of people's existing knowledge, attitudes, and emotions toward the company/brand, consider the antecedent of CE (Behnam et al. 2021; Dolan et al. 2016; Pansari and Kumar 2017), and allow this study to focus more on how people view AI that they first learn about and how their trust impact CE.

Although some scholars have studied how to promote CE through AI tools at the theoretical and experimental levels (Perez-Vega et al. 2021; Prentice, Weaven, and Wong 2020), that is not the focus of this study. This research prefers to understand from the perspective of ordinary people how much they trust AI and how their trust affects their customer engagement. Therefore, an online survey was conducted. An AI-based service that will launch on social media was introduced to participants through text descriptions and pictures, and the functions supported by this service were also explained. Then, questionnaires were used to collect their answers about their trust in AI-based service, their feelings about this service, and CE for the company/brand that uses the service.

The results show that when people do not know much about the company or brand, their feelings about AI will positively impact CE. Two dimensions of trust (trust based on quality assurance and risk-taking) in human-like AI-based services also positively impact CE. At the same time, feelings about AI will fully mediate the relationship between all three dimensions of trust in AI and CE, but only trust based on CSR has a negative impact on feelings.

This article has three main contributions. First, a scale for trust in Human-like AI-based service was developed. Considering that the general public still has an insufficient understanding of AI, a human-like AI-based service should be regarded as a whole trustee. This study divides trust into six components: confidence, competence, vulnerability, betrayal, affective motivation, and normative motivation (Ryan 2020). Further, these six components are merged into three: trust based on quality assurance (confidence, competence, and affective motivation), trust based on risk-taking (betrayal and vulnerability), and trust based on corporate social responsibility (normative motivation) (European Commission 2011; International Organization for Standardization 2005; Mayer, Davis, and Schoorman 1995). This scale proposes a more feasible measurement approach for trust in human-like AI and reminds researchers and business managers that using traditional methods, which are more appropriate for offering and brand, is not an excellent way to research trust in AI.

Second, this study provides a theoretical basis and supplement for trust in AI and the relationship between trust and CE. Although some studies have pointed out that AI is untrustworthy (Ryan 2020; Siau and Wang 2018), ordinary people may hold different views. To ensure the rigor of the research, this study will share the trust in AI among AI technology, technical teams (who develop and operate AI), and companies/brands (who supply AI service) to ensure that human-like AI is correctly trusted as a whole. Moreover, this study discusses the divergence in the impact relationship between trust and CE. Two reasons for this divergence are the nature of the "increment of volitional investment" of customer engagement and the difference of the trust agent. This article also provides theoretical support for the possible existence of mediating variables between trust in AI and CE. To ensure that the trustee is human-like AI-based services, people's knowledge about the company/brand is limited, and AI service is introduced only through text descriptions and pictures. In this way, people's trust in AI can affect CE basically only through their feelings about AI. The results show that people's trust in AI does affect their engagement with unfamiliar brands, with feelings playing a completely mediating role.

Third, this article helps managers better understand the importance of AI-based services and proposes ideas for how managers can provide AI-based services on social media. Although AI is making its way into people's daily lives, it is frustrating that many managers still need to learn how to use this emerging technology in their business, especially as a service (De Bruyn et al. 2020). This study shows that people who lack trust in the AI service will likely be less interested in the company/brand (even if the AI service has nothing to do with their main offerings). Therefore, when a company/brand wants to provide an AI service on social media, the company/brand needs to understand people's trust in the AI service. Meanwhile, although there is only a text description, an AI-based service is introduced in detail in the experiment, which could provide ideas on how companies could design their AI-based services. We should be aware that the popularity of AI-based services may further affect customers' purchase habits and future marketing and retailing (Jan, Ji, and Kim 2023).

## 2. Theoretical background

### 2.1. Customer Engagement (CE)

Although the early concept was referred to nearly two decades ago (Sawhney, Verona, and Prandelli 2005), customer engagement (CE) has only received much attention in the last decade. One fact is that the definition and concept of customer engagement are still under debate. However, there are still some commonalities about CE in those studies.

First, the nature of interaction and voluntary resource investment. In service-dominant logic, interaction is defined as "mutual or reciprocal action or influence" (Vargo and Lusch 2016). Interaction often occurs between customers and companies/brands, and CE reflects the voluntary resources customers invest in the company or brand (Behnam et al. 2021).

Second, multidimension. Though some CE research is unidimensional (e.g., customer engagement behaviors), most researchers treat CE as a multidimensional concept (Brodie et al. 2013; Kumar and Pansari 2016; Vivek et al. 2014). Three dimensions were adopted in this research: cognitive engagement (labeled as cognitive processing), emotional engagement (labeled as affection), and behavioral engagement (labeled as activation). Cognitive engagement is the level of brand-related thought processing and elaboration of the customer in interaction; emotional engagement is the degree of the customer's positive brand-related affection; behavioral engagement is the level of energy, effort, and time spent on a brand of the customer (Hollebeek, Glynn, and Brodie 2014). One thing to notice is that some researchers point out a fourth dimension: the social dimension (Hollebeek, Srivastava, and Chen 2019; Vivek et al. 2014), which is more related to the brand community. Since this study focuses on trust in Human-like AI and does not use an existing brand in the experiments, the dimension is not included.

Third, context-specific. Many studies have noticed that CE is context-specific (Bolton 2011; Brodie et al. 2011; Hollebeek, Srivastava, and Chen 2019). Both offline and online contexts have been studied in much research, and the result shows that CE will vary across contexts (Hollebeek, Srivastava, and Chen 2019). Because customer engagement on social media is a marketing outcome that cannot be ignored (de Oliveira Santini et al. 2020; Hollebeek, Glynn, and Brodie 2014; Simon and Tossan 2018; Wang and Kim 2017) and more research asking for enhancing CE through AI tools (Lim et al. 2022), research on CE in the digital context (AI-based and social media-related) and service context is necessary.

Since this study wants to reveal how people's trust in AI-based services on social media will affect CE, a definition of CE that is more appropriate for service is essential. Several researchers proposed that Service-dominate Logic (S-D logic) and customer engagement (CE) share a significant conceptual fit in the service context (Brodie et al. 2013; Hollebeek, Srivastava, and Chen 2019; Kumar et al. 2019). Then, this study will adopt the definition of Hollebeek, Srivastava, and Chen (2019), who define S-D logic-informed CE as "A customer's motivationally driven, volitional investment of focal operant resources (including cognitive, emotional, behavioral, and social knowledge and skills), and operand resources (e.g., equipment) into brand interactions in service systems."

As the impact of AI on CE in service interaction is still little known (Hollebeek, Sprott, and Brady 2021), the next thing to clarify is what kind of AI meets research requirements.

### 2.2. Artificial Intelligence (AI)

The frustrating fact is that the term "artificial intelligence" (AI), which is not a stranger to us, remains poorly defined (Kaplan and Haenlein 2019). The widely accepted definition of AI is intelligence demonstrated by machines (Shieber 2004). This definition is succinct but not precise enough for the service context.

Rust and Huang (2014) propose that AI is distinct from general information technology in that it involves technologies that can learn, connect, and adapt. Moreover, they delineated a strategic framework for using AI to engage customers for different services after several years of benefits (Huang and Rust 2021). In their framework, they emphasize that AI develops from mechanical, to thinking and to feeling, and each of the AIs can provide unique benefits to service for engaging customers. They also propose that the three AIs can be combined in various ways to cater to the nature of the service offering. Since this research focuses on AI that is more suitable in the service context on social media, thinking-feeling AI will be suitable.

Thinking-feeling AI, also marked as utilitarian relational service, involves intuitive AI and human intelligence (HI). Intuitive AI is one of the subtypes of thinking AI that can have bounded rationality and commonsense thinking, while feeling AI focuses more on engagement and interaction. For this type of AI, emotional connection with customers is unnecessary; on the contrary, human intelligence will play more of a role. It is not bad news as AI will not necessarily replace HI (/human employees); instead, they can work as a team (Wilson and Daugherty 2018). The Design of Experiment section will show more details about the AI-based service used in this article, which is designed based on this framework.

### 2.3. Trust

Human beings need to establish connections with many people and things throughout their lives, and trust is necessary to establish the most fundamental relationships (Ryan 2020). However, one thing that must be sure of is what exactly people trust.

#### 2.3.1. Customer engagement & trust

Just as the definition of CE is debated, research on the relationship between trust and CE is also under discussion. Some studies treat trust as an antecedent for CE (Jaakkola and Alexander 2014; Van Doorn et al. 2010; Youssef et al. 2018), while some others emphasize that trust should be viewed as a consequence of CE (Brodie et al. 2013; So et al. 2016a; Vivek, Beatty, and Morgan 2012). There are two possible reasons why this happens.

First, customer engagement is a concept that refers to the "increment of volitional investment." Despite the differences in definitions of CE, a trend in their wording could be found: A state of continuous increase. The state may be increased by continuous investment in psychology (ex., cognitive and affective), in behavior (ex., purchase), or based on community activity (ex., brand community, and social media) (Bowden 2009; Brodie et al. 2011; Harmeling et al. 2017; Hollebeek, Srivastava, and Chen 2019; Kumar et al. 2010; Kumar and Pansari 2016; Malthouse et al. 2016; Pansari and Kumar 2017; Van Doorn et al. 2010; Verleye, Gemmel, and Rangarajan 2014; Vivek, Beatty, and Morgan 2012). Then, studies on CE can be divided into two tendencies: "How to increase the increment?" and "What impact will this increase have." For "how to increase the increment," the most critical points are "how to interest the customer to invest more" and "what makes the customer invest more." For "what impact will this increase have?", as a customer's investment increases over a certain period, the customer already has a certain degree of focal operant and operand resources, further influencing the relationship between the customer and company/brand. Trust in these two tendencies is different: for the former, trust is more of a factor in attracting customers to engage; for the latter, it is more of the results of previous investments.

Second, the difference of the trust agent. While many studies use the term Trust, there are mainly three types of trust: source, brand, and customer trust. Source trust, often linked to social media and community, is always treated as an antecedent of CE. If customers have no prior knowledge about the company/brand or its offering, their trust in the source (e.g., News, Word-of-Mouth, Key Opinion leader) may enhance their engagement, as it leads to an increase in investment (Pansari and Kumar 2017). Brand trust, defined as the average consumer's willingness to rely on the ability of the brand to perform its stated function (Chaudhuri and Holbrook 2001), could be both antecedent and consequent of CE. If customers know the brand well, trust in the brand may influence engagement (Brodie et al. 2011), and after investment, trust in the brand will be influenced by the result of engagement (So et al. 2016a). Customer trust, commonly used in CE studies, generally combines trust in offerings and the company/brand. Trust here is always defined as "a willingness to rely on exchange partners (Moorman, Deshpande, and Zaltman 1993)". It is generated by a determination of customers' confidence in the quality and reliability of the offerings of the company/brand (Kumar et al. 2019).

AI-based services are selected as the agent of trust (which makes trust more based on the information source and the offerings themselves), and respondents' knowledge of the company/brand is limited in this study (which also makes it impossible for people's trust to be based on the existed company/brand itself) to ensure trust as an antecedent for CE. In most studies on the relationship between trust and CE, trust positively impacts CE, so this study will also assume that trust in AI will positively impact CE. Then, the next problem is whether AI or AI-based services can be trustees.

#### 2.3.2. Artificial intelligence & trust

Since AI began to enter the public eye, many researchers have begun to discuss the issue of trust in AI (Glikson and Woolley 2020; Jacovi et al. 2021, March; Siau and Wang 2018). One voice proposes that AI is not something we can trust.

Ryan (2020) proposed that AI cannot be trusted because of the definition of trust in Philosophy. He divided interpersonal trust into six dimensions (confidence, competence, vulnerability, betrayal, affective motivation, and normative motivation) based on three dominant trust paradigms (rational account, affective account, and normative account) to discuss if AI can be trusted (see Table 1). The rational account of trust mainly refers to people relying on an object to do something based on their rational predictions (O'Neill 2002; Tuomela and Hofmann 2003). The affective account of trust contains three elements: the trustee is motivated to act because of trust; the trustee has the trustor's interests at heart; and the trustee

*Table 1. Components and paradigms of trust.*

| | Trust paradigms | | | |
|---|---|---|---|---|
| Trust component | Rational | Affective | Normative | Description |
| Confidence | ° | ° | ° | The *expectations* the trustor has of the trustee have to be positive and favorable (Luhmann 1979). |
| Competence | ° | ° | ° | Trustees have the ability to do something, distinguished from [mere] hopefulness (Ryan 2020). |
| Vulnerability | ▲ | ° | ° | Trust is a willingness to be vulnerable to another party (Mayer, Davis, and Schoorman 1995); there is no need for trust in the absence of vulnerability (Hall et al. 2001). |
| Betrayal | | ° | ° | Trust will be breached, resulting in a cost to the trustor (Tuomela and Hofmann 2003); betrayal differs from *disappointment* (Fossa and Pisa 2019; Tavani 2015). |
| Affective Motivation | | ° | | The trustee has the trustor's interests at heart, and their actions are fundamentally based on and guided by a sense of goodwill toward the trustor (Jones 1996). |
| Normative Motivation | | | ° | What a trustee should do in a particular situation (Simpson 2012); Relates to responsibility and accountability. |

*Notes*: ▲ = Whether AI is vulnerable is different according to the type of AI. For example, AI autonomous driving may cause car accidents; however, an AI chatbot may not be able to harm us.

is motivated by goodwill toward the trustor (Jones 1996). Normative accounts of trust focus on what the trustee should do to maintain the relationship with the trustor and not violate the trustor's expectations (Simpson 2012). He claimed that AI can only be trusted in rational accounts and cannot be treated as a trustee in affective and normative accounts.

However, it must be recognized that no one can guarantee that ordinary people (vs. experts) have this knowledge or understanding of AI. Rather than expecting everyone to have the same knowledge of AI, developing a trust scale that caters to different levels of knowledge is more reasonable. Treating it as a complete trustee is more suitable for understanding various people's trust in human-like AI.

Since AI technology can only be trusted in rational accounts, it needs other parts of this trustee as the trust agent for affective and normative accounts. Technical teams and companies/brands become suitable choices because mechanisms should "be put in place to ensure responsibility and accountability for AI systems and their outcomes, both before and after their development, deployment and use" (Hleg 2019). Then, a human-like AI as a complete trustee should consist of three parts: AI technology, technical team (who develops and operates it), and company/brand (who provides it). The trustee was divided into three components instead of two because the company may use AI technology delivered by another company. The technical team and company/brand cannot be treated as the same, especially when AI causes problems; it is necessary to know whether it is caused by technical problems or improper use.

Regardless of whether people view human-like AI as an independent entity or an offering, when people lack knowledge of the company/brand that provides this service, trust in AI always meets the conditions of being an antecedent of CE. Therefore, we proposed that:

**H1.** *Trust in AI will positively influence customer engagement.*

### 2.4. Feelings about AI

The distinction between feelings and emotions has been a hot topic in psychology research, and many books and studies have discussed it in detail (Arnold 2013; Damasio 2004; Goldie 2000; Shouse 2005). However, this article will only point out the difference between feelings and emotions used in the study to ensure that it does not cause controversy.

Shouse (2005) defines feeling as "a sensation that has been checked against previous experiences and labeled," it is a very personal and biographical concept. Everyone's feelings are derived from their perceptions from past experiences, which prevents everyone from having the same ideas when looking at the same things. For a technology like artificial intelligence that is unfamiliar to the public, their feelings will naturally be different, and this difference mainly comes from their own life experiences and knowledge. An emotion is the projection/display of a feeling (Shouse 2005). Unlike feelings, emotion does not have to be based on experience and knowledge; it can directly express affect. There would be no emotion without certain feelings towards something (Goldie 2000). This difference means that feelings are more suitable than emotions for situations that require judgment based on experience.

Hence, even though emotions are treated as antecedents of customer engagement (de Oliveira Santini et al. 2020; Pansari and Kumar 2017), it is not an appropriate choice in this study. This paper intends to understand how people feel about AI services when they do not know the company/brand and cannot directly use the AI services. People may not have the same feelings toward unfamiliar things, like human-like AI or unknown companies/brands, so feelings about AI in this research are limited to preferences for the service and willingness to use it (e.g., feel good about it). Therefore, people need to judge this AI service based on their experiences, knowledge, and the information they were given. In this way, emotions based on knowledge and experience, that is, feelings, become a more appropriate choice.

Because customer engagement is about motivationally investing resources (like emotional resources and knowledge) into brand interaction and interacting with AI itself is also a form of brand interaction, we propose that:

**H2.** *People's feelings about the AI-based service will positively influence customer engagement.*

Emotion is considered one of the antecedent factors in CE research (Brodie et al. 2013) and a mediating variable between trust and CE (Pansari and Kumar 2017). Emotions here are "mental states of readiness that arise from cognitive appraisals of events or one's own thoughts" (Bagozzi, Gopinath, and Nyer 1999) and are more brand-related. Some researchers pointed out that although trust and emotion positively impact CE, there is no apparent relationship between them (de Oliveira Santini et al. 2020). However, the emotion involved in their study is entirely based on consumption experience, and the trustee is the community.

Although a human-like AI is viewed as the trustee in this study, it comprises AI technology, technical teams, and enterprises/brands. People's knowledge of companies/brands is limited to eliminate unnecessary interference because it is one of the antecedents of CE (Hollebeek, Srivastava, and Chen 2019; Sinkula, Baker, and Noordewier 1997). It helps more accurately understand how people will trust a human-like AI-based service that they do not understand or have experienced. In this situation, people's trust in AI affects their engagement more through their feelings about AI but not their understanding of the company/brand. Since this study argues that the general public views AI like professional researchers, people's feelings will be assumed to be experience-based and more emotional (rather than purely rational). This emotional investment in AI is why ordinary people's trust in AI affects CE. Therefore, we propose that:

**H3.** *Feelings about AI-based service fully mediate between trust in AI and customer engagement.*

## 3. Research methodology

In previous studies, customer knowledge, company size, type of social media, type of firm, and type of industry (/context) were proven to affect CE (Behnam et al. 2021; de Oliveira Santini et al. 2020; Hollebeek, Srivastava, and Chen 2019; Kumar et al. 2019; Pansari and Kumar 2017; Van Doorn et al. 2010). Therefore, during the introduction phase of the experiment, the company providing human-like AI-based services was introduced as "a large international clothing company" and referred to by the pseudonym "BKL company" to ensure that additional factors would not have an impact. In addition, the experiment selected a non-existent AI-based service (AI communicator "Minis_BKL") and non-existing social media to ensure that the subjects would not be affected. An AI-generated image was used as the avatar of AI to make it more human-like (see Appendix).

Considering that people have different understandings of AI, we introduced the functions of the AI-based service with text descriptions and pictures. The general content of the AI service functions introduced in the experiment can be found in Table 2 and the pictures in Appendix. Those functions can control the impact of differences in people's understanding of the AI-based service and allow subjects to judge whether they trust it better.

As shown in Table 2, seven items from the entire introduction of the experiment were extracted as options of screening question. This screening question is designed for two reasons: First, it is to screen the samples who did not read it carefully; Second, because the introduction is quite long, some people might forget part of it, and these items can help them recall what they had read before.

The questionnaire consists of six parts: screening questions, items for AI communicator (including hidden screening questions), items for CE, items for trust, an item for avatar of virtual characters, and Demographic items (43 items in total). Among them, 7-point Likert scales were used in items for AI communicator, CE, and trust (see Table 6.1).

The survey was conducted on WJX, one of the largest research websites in China. To ensure the authenticity and reliability of the data, WJX was entrusted with collecting samples. All IP addresses can participate only once to limit the repeated participation of subjects and ensure that all respondents can be

*Table 2. Screening questions and condition control.*

| Item | Item content | Condition control |
|---|---|---|
| SQ1.1 | This AI communicator will post information and announcements on social media, and all the contents are provided by the company. | Information Source |
| SQ1.2 | This AI communicator will answer questions about its company and brand, products and services, and other related topics. | Basic Function |
| SQ1.3 | This AI can carry out simple dialogue and communication. | Basic Communication Function |
| SQ1.4 | The content of the answer was generated by AI and is based on the database specially provided by the enterprise. | Information Source; Attribution of Responsibility |
| SQ1.5 | The data and information used by the AI communicator are filtered and verified by the company. | |
| SQ1.6 | This AI communicator will collect data and information about the company and its offerings and update the content in its database. | Continuously Updated |
| SQ1.7 | This AI communicator will send the content that is not contained in the database to the person in charge. | Work with Human Intelligence |

*Notes*: "All seven options are included in a multiple-choice question for screening samples."

*Table 3. Respondents' demographic profiles.*

| Characteristics | N (=296) | % |
|---|---|---|
| Gender | | |
| Male | 122 | 41.2 |
| Female | 173 | 58.4 |
| Other | 1 | 0.3 |
| Age(years) | | |
| under 18 | 2 | 0.7 |
| 18~25 | 27 | 9.1 |
| 26~35 | 185 | 62.5 |
| 36~45 | 64 | 21.6 |
| 46~60 | 18 | 6.1 |
| Education | | |
| Junior middle school or below | 1 | 0.3 |
| Senior high school or technical secondary school | 6 | 2.0 |
| Junior college | 26 | 8.8 |
| Bachelor | 237 | 80.1 |
| Postgraduate or above | 26 | 8.8 |
| Occupation | | |
| Business Manager | 81 | 27.4 |
| Administration | 39 | 13.2 |
| Technical Development/Engineer | 27 | 9.1 |
| Product/Operations | 25 | 8.4 |
| Marketing/Sales/Business | 17 | 5.7 |
| Finance/Accounting/Treasurer/Audit | 17 | 5.7 |
| Human Resource | 16 | 5.4 |
| Others | 74 | 25.0 |

*Notes*: There are 13 other occupations in the "Others" group.

traced to their source. In this way, a total of 495 questionnaires were collected. 199 questionnaires were eliminated mainly due to (1) incomplete answers, (2) timeout (more than 1 hour), (3) wrong answers to screening questions, and (4) giving opposite tendencies on similar items. In the end, 296 valid data remain (>5 times the number of items): 58 subjects selected no less than five options in the screening question, and 238 subjects selected all correct options (including selecting all seven options and "all of the above"). In subsequent testing, the results of multiple groups analysis in AMOS showed no difference between the two groups (the result of structural weights of Nested Model Comparisons: df = 29, CMIN = 32.435, p = .301), indicating that they can all be recognized as valid samples. Detailed demographics are provided in Table 3.

### 3.1. *Develop a scale of trust in human-like AI*

As the study is exploratory research, exploratory factor analysis (EFA) was conducted in SPSS to uncover the underlying structure and to examine internal reliability (see Fig. 1). The Cronbach's alpha

| Rotated Component Matrix[a] | Component | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Vulnerability_TT | **0.882** | 0.093 | 0.155 | 0.029 | -0.003 | -0.015 | 0.058 | 0.025 |
| Betrayal_C/B | **0.865** | 0.000 | 0.135 | 0.108 | 0.008 | -0.014 | -0.104 | 0.118 |
| Betrayal_TT | **0.858** | -0.010 | 0.140 | 0.020 | 0.056 | 0.042 | -0.021 | 0.025 |
| Vulnerability_C/B | **0.850** | 0.033 | 0.198 | 0.113 | -0.024 | -0.066 | -0.055 | 0.137 |
| Vulnerability_AI (Not accepted) | **0.807** | 0.010 | 0.173 | -0.015 | -0.033 | -0.027 | 0.170 | -0.001 |
| Betrayal_AI (Not accepted) | **0.793** | 0.062 | 0.161 | -0.074 | 0.006 | -0.025 | 0.116 | -0.252 |
| Confidence_TT | 0.059 | **0.776** | 0.005 | 0.194 | 0.115 | 0.096 | 0.232 | 0.079 |
| Confidence_AI | 0.018 | **0.752** | -0.034 | 0.182 | 0.294 | 0.109 | 0.036 | 0.070 |
| Confidence_C/B | 0.076 | **0.607** | 0.076 | 0.327 | 0.004 | 0.083 | 0.396 | 0.240 |
| Normative_Motivation_TT | 0.316 | 0.005 | **0.856** | 0.059 | 0.037 | 0.099 | -0.001 | 0.065 |
| Normative_Motivation_C/B | 0.346 | 0.008 | **0.849** | -0.022 | -0.011 | 0.073 | -0.062 | 0.080 |
| Normative_Motivation_AI (Not accpted) | 0.426 | 0.013 | **0.666** | -0.086 | -0.004 | -0.065 | 0.126 | -0.266 |
| Feelings_about_AI_1 | -0.069 | 0.222 | 0.102 | **0.836** | 0.069 | 0.077 | 0.023 | 0.090 |
| Feelings_about_AI_2 | 0.137 | 0.217 | -0.096 | **0.684** | 0.229 | 0.241 | 0.025 | 0.073 |
| Feelings_about_AI_3 | 0.163 | 0.165 | -0.095 | **0.641** | 0.274 | 0.142 | 0.383 | 0.050 |
| Competence_C/B | 0.009 | 0.211 | -0.015 | 0.130 | **0.815** | 0.147 | 0.151 | 0.032 |
| Competence_TT | -0.056 | 0.111 | 0.030 | 0.252 | **0.729** | 0.079 | 0.217 | 0.218 |
| Competence_AI | 0.049 | 0.506 | 0.051 | 0.093 | **0.540** | 0.154 | -0.215 | 0.247 |
| AI_Future2 | -0.086 | -0.051 | 0.040 | 0.196 | 0.156 | **0.759** | 0.154 | 0.111 |
| AI_Future3 | -0.027 | 0.204 | 0.030 | 0.049 | 0.223 | **0.741** | 0.171 | -0.145 |
| AI_Future1 | 0.013 | 0.186 | 0.068 | 0.130 | -0.096 | **0.668** | -0.217 | 0.305 |
| Affective_Motivation_AI (Not accepted) | 0.091 | 0.279 | 0.014 | 0.136 | 0.221 | 0.086 | **0.738** | 0.173 |
| Affective_Motivation_TT | 0.071 | 0.260 | -0.023 | 0.116 | 0.280 | 0.086 | 0.198 | **0.710** |
| Affective_Motivation_C/B | 0.006 | 0.205 | 0.027 | 0.179 | 0.255 | 0.289 | 0.444 | **0.508** |

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 10 iterations.

| KMO and Bartlett's Test | | |
|---|---|---|
| KMO Measure of Sampling Adequacy. | | **0.862** |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 3755.793 |
| | df | 276 |
| | Sig. | 0 |

*(Notes: eigenvalues= 0.8; Components with initial eigenvalues less than 1.0 are the components 6 (.928), 7(.894), and 8(.803); "Not accepted" means AI cannot be regarded as a trustee from these dimensions of trust; TT= Technical Team, C/B=Company/Brand, AI= artificial intelligence.)*

*Fig. 1. Result of exploratory factor analysis (EFA).*

coefficient result was 0.862 ($p < 0.001$), ensuring reliability. Moreover, the CE scale has also proven reliable (Cronbach's alpha = 0.94, $p < 0.001$). There are three components whose eigenvalues are less than 1: component 6 (labeled as "Future of AI-based service"), component 7 (labeled as "Affective motivation of AI technology"), and component 8 (labeled as "Affective motivation of human-like AI"). Items for the future of AI are only used to observe people's opinions on whether such AI-based services will become familiar and will not be factored into subsequent research models. The eigenvalue of affective motivation is less than 1, which may be caused by a lack of items and respondents' lack of knowledge of the technical team and the company. Since it is an essential component of trust, those items are still adapted. The items of betrayal and vulnerability are classified as the same factor, possibly due to the lack of items and the fact that the AI-based service in this study is less vulnerable to respondents. Four items of trust in AI were not accepted because AI technology cannot be a correct agent among these four types of trust.

Confirmatory factor analysis (CFA) was conducted to verify the reality and validity of the items and to confirm whether there are latent variables in the six components of trust. The AVE of competence and affective motivation are slightly lower than 0.5. It may be caused by the lack of items, respondents' lack of knowledge of the company, and the difference between people's origin AI-related knowledge. This study will treat them as influential factors since Formell and Larcker (1981) point out that if CR is greater than 0.6, then as long as AVE is greater than 0.36, the convergent validity of the construct is still adequate. The result shows that affective motivation is highly correlated with confidence, competence, and normative motivation, and betrayal is highly correlated to vulnerability. It means there are latent second-order factors, so CFA was conducted again to verify conjecture (see Tables 4.1 and 4.2).

As shown in Tables 4.1 and 4.2, the six components of trust are reduced to three dimensions: trust based on quality assurance, trust based on risk-taking, and trust based on corporate social responsibility. For

*Table 4.1. Convergent validity of Trust in AI (Second-order).*

| Second-order variable | Latent variable (factor loading) | Items | Factor loading | Error variance | CR | CR (second-order) | AVE | AVE (second-order) |
|---|---|---|---|---|---|---|---|---|
| Quality Assurance | Confidence (0.831) | AI | 0.706 | 0.413 | 0.775 | 0.911 | 0.534 | 0.774 |
| | | TT | 0.753 | 0.354 | | | | |
| | | C/B | 0.733 | 0.441 | | | | |
| | Competence (0.838) | AI | 0.606 | 0.603 | 0.744 | | 0.495 | |
| | | TT | 0.746 | 0.416 | | | | |
| | | C/B | 0.749 | 0.464 | | | | |
| | Affective Motivation (0.964) | TT | 0.664 | 0.569 | 0.629 | | 0.459 | |
| | | C/B | 0.691 | 0.561 | | | | |
| Risk-taking | Betrayal (0.959) | TT | 0.851 | 0.798 | 0.867 | 0.965 | 0.765 | 0.933 |
| | | C/B | 0.898 | 0.617 | | | | |
| | Vulnerability (0.973) | TT | 0.907 | 0.527 | 0.905 | | 0.827 | |
| | | C/B | 0.912 | 0.521 | | | | |
| Corporate Social Responsibility (Normative Motivation) | | TT | 0.856 | 0.601 | | 0.890 | | 0.802 |
| | | C/B | 0.934 | 0.308 | | | | |

*Notes*: AI = AI technology itself, TT = Technical Team, C/B = Company/Brand; CR = Composite Reliability, AVE = Average Variance Extracted; Model fit: $\chi^2$/df = 1.826, GFI = 0.947, AGFI = 0.919, NFI = 0.943, NNFI(TLI) = 0.965, CFI = 0.973, SRMR = 0.042, RMSEA = 0.053.

*Table 4.2. Discriminant validity (second-order).*

| | (1) | (2) | (3) |
|---|---|---|---|
| Trust based on Quality Assurance (1) | 0.880 | | |
| Trust based on Risk-taking (2) | 0.124 | 0.966 | |
| Trust based on Corporate Social Responsibility (3) | 0.081 | 0.558 | 0.896 |

quality assurance, the International Organization for Standardization (International Organization for Standardization 2005) defines it as "part of quality management focused on providing *confidence* that quality requirements will be fulfilled." The three components of trust based on quality assurance are confidence, competence, and affective motivation. Confidence shows the trustor's expectation, competence is based on the ability of AI-based service (mainly on the technology level), and affective motivation means that customers believe the technical team and company/brand always have the trustor's interests at heart and have goodwill to them.

Risk-taking is defined as the trustor's willingness to be *vulnerable* to the trustee's actions based on expectation (Mayer, Davis, and Schoorman 1995) and as engagement in behaviors associated with some probability of undesirable results (Boyer 2006). Trust based on Risk-taking includes betrayal and vulnerability.

Corporate social responsibility is defined as the responsibility of enterprises for their impact on society (European Commission 2011). For an individual, normative motivations may be ordinary moral principles or a sense of responsibility toward other people or things. However, a human-like AI is not a correct trust agent, so the technical team and company/brand should assume these responsibilities and corporate social responsibility will be a more appropriate term. Then, the hypotheses should be revised:

**H1.** *Trust in AI will positively influence customer engagement.*

**H1a.** *Trust based on quality assurance will positively influence customer engagement.*

**H1b.** *Trust based on risk-taking will positively influence customer engagement.*

**H1c.** *Trust based on corporate social responsibility will positively influence customer engagement.*

Moreover, H3 will also be revised in the same way:

**H3.** *Feelings about AI-based service fully mediate between trust in AI and customer engagement.*

**H3a.** *Feelings about AI-based service fully mediates between trust based on quality assurance and customer engagement.*

**H3b.** *Feelings about AI-based service fully mediates between trust based on risk-taking and customer engagement.*

**H3c.** *Feelings about AI-based service fully mediates between trust based on corporate social responsibility and customer engagement.*

*Table 5. Direct and total effects.*

| Structural equation modeling | | N = 296 | | | | |
|---|---|---|---|---|---|---|
| Direct effect | | standard $\beta$ | S.E. | C.R. | p-value | Remark |
| Feelings => CE | | 0.953 | 0.073 | 11.79 | *** | H2 supported |
| Fit Indices: $\chi^2$/df = 2.131, GFI = .973, AGFI = .906, NFI = .940, NNFI(TLI) = .958, CFI = .967, RMR = .040, SRMR = .034, RMSEA = .062 | | | | | | |
| Trust => CE | QA => CE | 0.781 | 0.123 | 8.751 | *** | H1a supported |
| | Risk-Taking => CE | 0.195 | 0.034 | 3.138 | 0.002** | H1b supported |
| | CSR => CE | −0.088 | 0.037 | −1.449 | 0.147 (n.s.) | H1c unsupported |
| Fit Indices: $\chi^2$/df = 2.043, GFI = .881, AGFI = .850, NFI = .888, NNFI(TLI) = .929, CFI = .939, RMR = .068, SRMR = .047, RMSEA = .059 | | | | | | |
| Total effect | | standard $\beta$ | S.E. | C.R. | p-value | Remark |
| Trust => CE (Direct) | QA => CE | 0.045 | 0.18 | 0.342 | 0.732 (n.s.) | No direct influence |
| | Risk-Taking => CE | 0.039 | 0.032 | 0.686 | 0.493 (n.s.) | |
| | CSR => CE | 0.042 | 0.034 | 0.756 | 0.45 (n.s.) | |
| Trust => Feelings | QA => Feelings | 0.811 | 0.138 | 8.967 | *** | H3a supported |
| | Risk-Taking => Feelings | 0.17 | 0.042 | 2.456 | 0.014* | H3b supported |
| | CSR => Feelings | −0.141 | 0.046 | −2.075 | 0.038* | H3c supported |
| Feelings => CE | | 0.909 | 0.139 | 5.895 | *** | (Full Mediation) |
| Fit Indices: $\chi^2$/df = 1.999, GFI = .868, AGFI = .837, NFI = .877, NNFI(TLI) = .924, CFI = .934, RMR = .065, SRMR = .046, RMSEA = .058. | | | | | | |

*Notes*: Feelings = Feelings about AI-based service; QA = Quality Assurance; CSR = Corporate Social Responsibility, CE = Customer Engagement; ***p < .001, **p < .01, *p < .05, n.s. = not significant.

## 4. Results

CFA was conducted to verify the model, and the result shows a high correlation between feelings about AI and customer engagement and between feelings about AI and trust based on quality assurance. The following reasons may cause it: respondents cannot use the AI-based service and lack knowledge of the company and brand, making them more likely to judge based on their feelings. Based on this, it would be easy to understand why the convergent validity of feelings (AVE = 0.496) is slightly lower than 0.5 (see Table 6.1). However, it can still be treated as a valid factor because the correlation between feelings and the other two dimensions of trust in AI is low. Meanwhile, feelings about AI are more focused on AI service, but the affective part of CE is related to the company/brand, which makes feelings about AI could be treated as a separate factor. More details of CFA results and item descriptions are shown in Tables 6.1 and 6.2.

As shown in Table 5, Feelings about human-like AI-based service significantly influenced customer engagement ($\beta = 0.953$, SE = .073, $p < 0.001$), supporting H2. For Trust in AI, trust based on quality assurance and risk-taking both have a significant impact on customer engagement ($\beta = 0.781$, SE = .123, $p < 0.001$; $\beta = 0.195$, SE = .034, $p < 0.005$), supporting H1a and H1b; however, trust based on CSR had no significant influence on customer engagement, which means H1c is not supported. The possible reason is that respondents lack understanding of the company/brand and the technical team, or a lack of items causes it. It may also be due to people's knowledge of AI because the more people understand AI, the less likely they are to trust companies to be responsible for it, and their lack of knowledge of companies/brands makes them unwilling to engage.

Regarding the mediating effect, feelings about AI significantly mediate between trust in AI and customer engagement. Since all three dimensions of trust in AI do not significantly influence customer engagement, feelings about AI can also be confirmed as a fully mediating factor. As shown in Table 5, H3a, H3b, and H3c are supported. One thing to notice is that trust based on CSR negatively influences feelings about AI. It may be caused by the subject's lack of knowledge of the company/brand and technical team. People who believe that corporate social responsibility is essential may be less likely to be emotional, thus suppressing their positive evaluation of AI services and further inhibiting their engagement.

## 5. General discussion

With the development of AI technology, AI services for the general public have gradually received people's expectations. The result shows that people have a favorable view of the AI communicators mentioned in the experiment and believe that they will become widely available shortly (Mean $_{\text{(future of AI)}}$ = 5.95, SD = 0.783, see Table 6.1). However, contrary to the fact, academics and business managers are not sufficiently

*Table 6.1. Measurement items and convergent validity of construct.*

| Construct | Factor loading | Source |
|---|---|---|
| Feelings about AI (CR = 0.745, AVE = 0.496) | | |
| ° I think this AI-based service is good. | 0.614 | |
| ° I like this AI-based service. | 0.699 | New |
| ° I would be happy to use this AI-based service. | 0.789 | |
| CE: Cognitive Processing (CR = 0.821, AVE = 0.604) | | |
| ° I think using this AI communicator service will get me to think about BKL company. | 0.77 | |
| ° I would think about BKL company a lot if I could use the AI communicator service. | 0.787 | |
| ° I think using the AI communicator service will stimulate my interest in learning more about BKL company. | 0.775 | |
| CE: Affection (CR = 0.841, AVE = 0.570) | | |
| ° I think I will feel very positive if I use the AI communicator service of BKL company. | 0.756 | |
| ° I think using the AI communicator service of BKL company makes me happy. | 0.717 | Behnam et al. (2021); Hollebeek, Glynn, and Brodie (2014) |
| ° I think I would feel good if I used the AI communicator service of BKL company. | 0.763 | |
| ° I think I will be proud to use the AI communicator service of BKL company. | 0.782 | |
| CE: Activation (CR = 0.784, AVE = 0.548) | | |
| ° If possible, I will spend a lot of time experiencing the services/products of BKL company compared to other companies/brands that don't support AI communicator service. | 0.734 | |
| ° If possible, whenever I use clothes-related services/products, I use the services/products of BKL company. | 0.751 | |
| ° If possible, BKL company will be one of the companies/brands I will use when I want to purchase clothes or experience related services. | 0.736 | |
| Customer Engagement (CE, second-order) (CR = 0.784, AVE = 0.548) | | |
| CE: Cognitive Processing | 0.967 | |
| CE: Affection | 0.927 | NA |
| CE: Activation | 0.977 | |
| QA: Confidence (CR = 0.774, AVE = 0.534) | | |
| ° I have confidence in the AI technology itself and think it can ensure the completion of the tasks mentioned in the introduction. | 0.703 | |
| ° I have confidence in the technical team and think they will ensure that the AI can complete the tasks mentioned in the introduction. | 0.748 | Luhmann (1979); Ryan (2020) |
| ° I have confidence in the company/brand and think they will ensure that the AI can complete the tasks mentioned in the introduction. | 0.74 | |
| QA: Competence (CR = 0.744, AVE = 0.495) | | |
| ° I believe that the capabilities of AI technology itself are sufficient to complete the tasks mentioned in the introduction. | 0.607 | |
| ° I believe that the capabilities of the technical team are sufficient to ensure that AI completes the tasks mentioned in the introduction. | 0.742 | Ryan (2020) |
| ° I believe that the capabilities of the company/brand are sufficient to ensure that AI completes the tasks mentioned in the introduction. | 0.752 | |
| QA: Affective Motivation (CR = 0.630, AVE = 0.460) | | |
| ° Because the AI technology itself wants to maintain its goodwill in my mind, I think it will complete the tasks mentioned in the introduction. | Not accepted | |
| ° Because the technical team wants to maintain their goodwill in my mind, I think they will make sure the AI completes the tasks mentioned in the introduction. | 0.653 | Jones (1996); Ryan (2020) |
| ° Because the company/brand wants to maintain their goodwill in my mind, I think they will make sure the AI completes the tasks mentioned in the introduction. | 0.703 | |
| Trust based on Quality Assurance (QA, second-order) (CR = 0.905, AVE = 0.760) | | |
| QA: Confidence | 0.875 | |
| QA: Competence | 0.842 | NA |
| QA: Affective Motivation | 0.902 | |
| Risk-taking: Betrayal (CR = 0.774, AVE = 0.534) | | |
| ° I would consider myself betrayed by the AI technology itself if it fails to complete the tasks described. | Not accepted | |
| ° I would consider myself betrayed by the technical team if the technical team failed to ensure that the AI completed the tasks in the introduction. | 0.851 | Fossa and Pisa (2019); Ryan (2020); Tavani (2015); Tuomela and Hofmann (2003) |
| ° I would consider myself betrayed by the company/brand if the technical team failed to ensure that the AI completed the tasks in the introduction. | 0.897 | |

*(Continued on next page)*

*Table 6.1. (Continued).*

| Construct | Factor loading | Source |
|---|---|---|
| Risk-taking: Vulnerability (CR = 0.905, AVE = 0.827) | | |
| ° If the AI service causes problems, I will be hurt because the AI technology itself fails to meet expectations. | Not accepted | |
| ° If the AI service causes problems, I will be hurt because the technical team failed to meet expectations. | 0.907 | Hall et al. (2001); Mayer, Davis, and Schoorman (1995); Ryan (2020) |
| ° If the AI service causes problems, I will be hurt because the company/brand failed to meet expectations. | 0.912 | |
| Trust based on Risk-taking (second-order) (CR = 0.965, AVE = 0.933) | | |
| Risk-taking: Betrayal | 0.962 | |
| Risk-taking: Vulnerability | 0.97 | NA |
| Trust based on Corporate Social Responsibility (CSR, normative motivation) (CR = 0.892, AVE = 0.806) | | |
| ° If AI services cause problems, I think the AI technology itself will be responsible for them and bear the corresponding responsibilities. | Not accepted | |
| ° If AI services cause problems, I think the technical team will be responsible for them and bear the corresponding responsibilities. | 0.844 | European Commission (2011); Ryan (2020); Simpson (2012) |
| ° If AI services cause problems, I think the company/brand will be responsible for them and bear the corresponding responsibilities. | 0.948 | |
| Other Items | | |
| Future of AI | | |
| ° I think this kind of AI-based communicator/service will become common in the near future. | | |
| ° I think this kind of AI-based communicator/service will become a norm on social media in the near future. | Mean = 5.95, SD = 0.783 | New |
| ° I think this kind of AI-based communicator/service will be used in various industries in the near future. | | |

*Table 6.2. Discriminant validity of construct (second-order).*

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| QA (1) | 0.872 | | | | |
| Risk-taking (2) | 0.126 | 0.966 | | | |
| CSR (3) | 0.074 | 0.554 | 0.898 | | |
| Feelings (4) | 0.822 | 0.126 | 0.013 | 0.704 | |
| CE (5) | 0.799 | 0.245 | 0.079 | 0.954 | 0.957 |

*Notes*: QA = Quality Assurance; CSR = Corporate Social Responsibility; CE = Customer Engagement.

prepared. According to the report of Elsevier (2024), although most academic and funding leaders agree on the importance of AI research, only a small number of them say they are ready to meet the challenge. Therefore, more research from different perspectives on how the application of AI will affect modern life is asked.

### 5.1. Theoretical implications

This article demonstrates a research idea for enhancing customer engagement through AI and responds to previous CE studies' suggestions for follow-up research directions (Hollebeek, Sprott, and Brady 2021; Lim et al. 2022).

This study has several theoretical implications. First, this study provides a theoretical basis for trust in AI. Although some studies have pointed out that AI itself is not an object that can be trusted (Ryan 2020; Siau and Wang 2018), this does not prevent many people from still trusting it, like trusting a human. Among the four items that were not included in trust in AI, the result of the affective motivation of AI technology showed that people trusted AI technology itself as if it were an independent individual (Mean = 5.60, SD = 1.056, the content of the item seen in Table 6.1). It also proves that ordinary people's trust in human-like AI differs from what many professional researchers expected and is a topic worthy of separate study. To ensure the rationality of trust in AI, this study regards human-like AI as a complete trustee, and the trust is jointly borne by AI technology, technical teams, and companies/brands. It ensures that AI technology will not be treated as a wrong trusted object and that people's trust in AI is correctly shared. This study refers to the philosophical definition of trust. It divides people's trust in AI into six dimensions (confidence, competence, vulnerability, betrayal, affective motivation, and normative motivation). Further, it reduces it to three dimensions: trust based on quality assurance, risk-taking, and corporate social responsibility (CSR).

This study provides a theoretical basis for subsequent research on trust in AI, ensuring that trust in AI is a concept that can be studied. It also provides a feasible idea and direction for subsequent research on trust in AI.

Second, this study provides a further theoretical supplement to the influence relationship between trust and CE. The influence relationship between trust and CE has always been a hot topic in CE research, but this also leads to disagreements and controversies in their influence relationship. This study explores the possible reasons for this divergence: the nature of the "increment of volitional investment" of customer engagement and the difference of the trust agent. For the nature of the "increment of volitional investment," there are two tendencies: "How to increase the increment" (Pansari and Kumar 2017) and "What impact will this increase have" (So et al. 2016a). Trust is always treated as an antecedent in the former and a consequent later. For the agent of trust, there are three main types of trust: source trust (information from others rather than a company), customer trust (trust in companies, brands, and/or their offerings), and brand trust. Source trust is usually regarded as an antecedent of CE because the object of trust is not the enterprise/brand (Hollebeek, Srivastava, and Chen 2019). Brand trust varies depending on the customer's understanding of the brand (Brodie et al. 2011), while customer trust varies depending on the focus. Recognizing this divergence is necessary to make research on the relationship between trust and CE more robust. To ensure that trust in AI serves as an antecedent of CE, this study explicitly limits people's knowledge of the company/brand, which makes people's trust more derived from the introduction in the experiment (one type of source trust) and trust in the service itself (which is unrelated to the company/brand providing the offerings). In subsequent studies on the impact relationship between trust and CE, we should ensure that the impact relationship between trust and CE is correctly understood to make the research results more convincing.

Third, this study provides a theoretical basis for the potential mediating variables between trust and CE. In this study, the subjects did not know the company/brand and had not experienced the AI-based service (they only learned about it through text descriptions and pictures). However, they still became interested in the company/brand that provided the AI service, and their trust in AI did positively affect CE. This trust is based on people's feelings about AI, which are emotions based on people's experience and knowledge (the high correlation between feelings and CE and the result of affective motivation of AI technology can prove this). At the same time, the experimental results show that trust based on CSR has no apparent direct impact on CE but negatively impacts feelings about AI. This conclusion means the relationship between people's trust in whether companies/brands providing AI services will assume social responsibility and CE needs further discussion. This study provides a new theoretical basis for subsequent researchers to study potential mediating variables between trust and CE and new directions and focuses for subsequent research.

### *5.2. Managerial implications*

The research generated several managerial implications. First, this article provides business managers with a trust scale for AI. This scale can help practitioners better understand people's trust in AI and address the "AI itself cannot be trusted" issue by dividing the trust agent into three components. Moreover, this scale allows practitioners to better realize the limitations of AI technology rather than viewing AI as an independent individual that can be fully trusted. It can prevent a recurrence of a situation like the one in 2022, where Air Canada believed that problems caused by AI services should be borne by AI service itself (Yagoda 2024, February 23). The results of this study also show that people's trust based on CSR will inhibit people's feelings towards AI. It means that whether or not a company will be responsible for the behavior of AI is an essential criterion for people to judge whether a company and AI are trustworthy. Companies should better understand their responsibilities and obligations in AI services to ensure that problems do not arise due to the wrong placement of trust.

Second, this study demonstrates to business managers and practitioners that people's trust in AI affects their engagement. The research repeatedly emphasizes the lack of understanding of companies/brands, which means that people's trust in AI is entirely based on their feelings about the AI service itself introduced in the experiment, and this feeling is only generated through text and pictures. The company mentioned in the experiment does not exist, and it is set as a large clothing company, meaning that AI services are not its primary offerings. However, even so, people have shown interest in this unfamiliar company/brand because of the AI-based service, promoting their engagement. Managers should realize that supplying AI services is not just about adding a channel to facilitate customers; it can also enhance customer engagement.

Third, this study provides a feasible AI service design idea. This study limits people's understanding of the company/brand, so people's trust (trust in the AI technology, the technical team, and the company/brand) and feelings come mainly from this non-existent human-like AI-based service. Some research points out that different types of AI technologies (such as autonomous driving) or AI services (such as purchasing wizards) may produce different results, and actual experiences may also affect the results (Perez-Vega et al. 2021; Xiao and Kumar 2021). Considering that many companies do not supply AI services because they do not know how to use AI, the AI services designed in this study can provide some tips (Elsevier 2024). At the same time, business managers should realize that people are confident about the future of AI services. AI services will change people's information retrieval methods and consumption habits again. Providing AI services as early as possible is not a wrong choice.

### 5.3. *Limitations and further research*

As with all exploratory research, limitations are inevitable. First, the new scale to trust in AI still needs optimization. The lack of items is the most apparent problem; further research should consider adding more items to verify this scale. The vulnerability of AI is limited in this research; however, it does not fit the whole picture. Follow-up research should re-verify this part in AI services or applications that may cause harm. In the experiment, respondents' knowledge of the company/brand is limited, influencing the result since customer knowledge is one of the antecedents of customer engagement (Behnam et al. 2021; Hollebeek, Srivastava, and Chen 2019). Another problem is whether social media (where to use it) should be the fourth component of AI trustee; subsequent research should consider this.

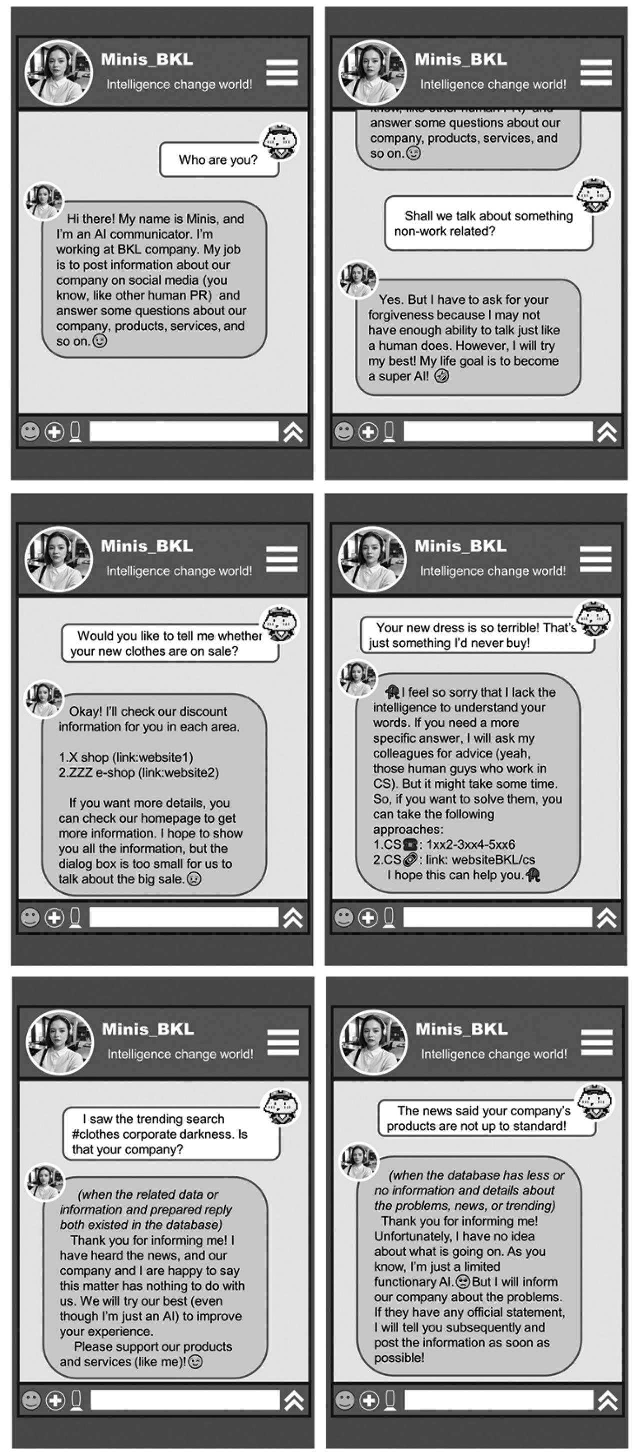
Second, feelings about AI are the only mediator selected in this research. The results show that feelings highly correlate with trust based on quality assurance and customer engagement. Other potential mediating variables may also cause it. Future research should explore this possibility. Meanwhile, even if people know that AI cannot be trusted, they will always have excessive expectations for this artificial existence. It is also a direction worth studying in customer engagement.

Third, the experiment itself will have limitations. As mentioned before, the AI service was introduced to the subjects with three pictures and long text descriptions, and there were many control conditions in the experiment. The following research should consider inviting people to experience AI services from existing companies or brands to verify the results. We should also notice that all subjects were Chinese or were located in China, which may also affect the experimental results. More research is expected to be conducted in different countries and regions.

## Conflict of interests

The authors declare no conflict of interest.

## Appendix: Pictures used in the experiment



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