The effect of required warmth on consumer acceptance of artificial intelligence in service

Peng, Chenming; van Doorn, Jenny; Eggers, Felix; Wieringa, Jaap E.

Published in:
International Journal of Information Management

DOI:
10.1016/j.ijinfomgt.2022.102533

Publication date:
2022

International Journal of Information Management 66 (2022) 102533

Contents lists available at ScienceDirect

International Journal of Information Management

journal homepage: www.elsevier.com/locate/ijinfomgt

Research article

The effect of required warmth on consumer acceptance of artificial intelligence in service: The moderating role of AI-human collaboration

Chenming Peng [a,b,c,*], Jenny van Doorn [c], Felix Eggers [d], Jaap E. Wieringa [c]

[a] Business School, University of International Business and Economics, China
[b] School of Economics and Management, University of Chinese Academy of Sciences, China
[c] Faculty of Economics and Business, University of Groningen, the Netherlands
[d] Department of Marketing, Copenhagen Business School, Denmark

ARTICLE INFO

Keywords:
AI acceptance
Required warmth
AI-human collaboration
AI service

ABSTRACT

Recent technological advances allow artificial intelligence (AI) to perform tasks that require high warmth, such as caring, understanding others' feelings, and being friendly. However, current consumers may be reluctant to accept AI for such tasks. This research investigates the impact of required warmth to conduct a task on consumer acceptance of AI service and the moderating role of AI-human collaboration. A series of choice-based conjoint experiments and one survey yield two main findings. First, consumers tend to refuse AI for tasks that require high warmth due to the low perceived fit between AI and the task at hand. Second, an AI-human collaboration of AI supporting a human employee increases consumer acceptance of AI service for tasks that require high warmth. This is not the case for AI-human collaboration in which AI performs a task that is supervised by a human employee. Theoretically, this study increases our understanding of how consumer acceptance of AI service varies across tasks and how AI-human collaboration can advance AI acceptance. These findings provide insightful suggestions for managers regarding designing AI service and framing AI-human collaboration.

1. Introduction

Artificial intelligence (AI) is exerting a transformative force on company business models, offerings, and processes (Borges, Laurindo, Spínola, Gonçalves, & Mattos, 2021; Collins, Dennehy, Conboy, & Mikalef, 2021; Davenport, Guha, Grewal, & Bressgott, 2020; Duan, Edwards, & Dwivedi, 2019; Dwivedi & Ismagilova, 2021; Huang & Rust, 2021b). AI—the intelligence manifested by machines using algorithms or statistical models in an embodied or non-embodied form—is increasingly replacing human workers in serving people throughout numerous industries (Autor & Dorn, 2013; Huang & Rust, 2018; Mende, Scott, van Doorn, Grewal, & Shanks, 2019; Mikalef & Gupta, 2021; Wang, Teo, & Janssen, 2021). The recent COVID-19 pandemic has even speeded up the process of the integration of AI in service provision (Coombs, 2020; Dwivedi et al., 2020). Due to the rapid development over the last decades, AI has recently started to undertake tasks that require warmth to some degree—a dimension of social perception that captures emotional traits such as caring, understanding others' feelings, and being friendly (Fiske, Cuddy, & Glick, 2007; Gelbrich, Hagel, & Orsingher, 2021; Kim, Schmitt, & Thalmann, 2019; van Doorn et al., 2017). Examples of these include, AI providing emotional support (Gelbrich et al., 2021) and assessing consumer feelings (Sidaoui, Jaakkola, & Burton, 2020). AI is predicted to master feelings just as well as humans in the foreseeable future (Huang & Rust, 2018; Huang, Rust, & Maksimovic, 2019; Rust & Huang, 2021). However, from a consumer perspective, AI may not be currently acceptable for all types of tasks (Castelo, Bos, & Lehmann, 2019)—especially tasks that require warmth—as AI is believed to not truly understand feelings at the moment (Ho, Hancock, & Miner, 2018). Against this backdrop, an empirical examination on consumer acceptance of AI for tasks that require warmth is needed.

Letting AI collaborate with human workers may help increase consumer acceptance of AI for tasks that require warmth. In particular, scholars have observed that the use of AI on a single task instead of taking over a whole job seems acceptable and does not require AI to assume all the tasks of said job (Brynjolfsson & Mitchell, 2017; Brynjolfsson, Mitchell, & Rock, 2018; Huang et al., 2019). Therefore, there is an opportunity for humans and AI to collaborate with each other on different tasks to satisfy consumers (Duan et al., 2019; Dwivedi, Hughes et al., 2021; Huang &, 2021a, 2021b; Huang et al., 2019; Xiao & Kumar,

* Corresponding author at: Business School, University of International Business and Economics, China.
E-mail addresses: chenming.peng@rug.nl (C. Peng), j.van.doorn@rug.nl (J. van Doorn), fe.marktg@cbs.dk (F. Eggers), j.e.wieringa@rug.nl (J.E. Wieringa).

https://doi.org/10.1016/j.ijinfomgt.2022.102533
Received 11 July 2021; Received in revised form 18 April 2022; Accepted 20 May 2022
Available online 2 June 2022
0268-4012/

2021; Zhang, Pee, & Cui, 2021). However, the collaboration does not only need to be in terms of AI and humans dividing tasks, but can also entail that both actors are working on the same task, for example, a human might perform the task and be supported by AI (e.g., a human driver with AI-based lane departure warning; Longoni, Bonezzi, & Morewedge, 2019; Longoni & Cian, 2020; Luo, Qin, Fang, & Qu, 2021; McLeay, Osburg, Yoganathan, & Patterson, 2021; Wesche & Sonderegger, 2019). Alternatively, AI may conduct the task under the supervision of a human (e.g., an autonomous driver with a human taking over in emergencies; Bansal & Kockelman, 2018; Wang & Lewis, 2007). Complementing human workers with AI may mitigate the disadvantages of AI. Longoni et al. (2019) discerned that consumers are less reluctant to adopt medical AI for the healthcare service when it offers helpful information to a human physician than when it fully replaces the human physician.

Prior studies have started to consider what warmth-related task features can determine AI acceptance and explore the role of AI-human collaboration in AI acceptance. However, two major research gaps remain. First, scholars have not theorized and empirically examined what type of AI-human collaboration, if any, is most preferred, for instance, whether collaboration with a human can foster consumer acceptance of AI across all types of tasks or whether this critically depends on the warmth that a task requires. Second, research on how consumers accept AI vis-à-vis tasks that require warmth is still limited. On the one hand, some studies have explored this question from the coworker perspective (e.g., Sampson, 2021; Waytz & Norton, 2014) but workers and consumers assess AI replacement from different standpoints and thus have dissimilar levels of AI acceptance (Granulo, Fuchs, & Puntoni, 2019). On the other hand, existing task features are related but not identical to warmth. For instance, social tasks are defined to be strongly associated with human expertise (Hertz & Wiese, 2019) but human expertise covers both emotional intelligence and intuitive intelligence (Huang & Rust, 2018). Castelo et al. (2019) similarly stated that subjective (vs. objective) tasks contain intuitive intelligence. On the contrary, warmth refers to emotional traits and mainly corresponds to emotional intelligence (Kim et al., 2019; Waytz & Norton, 2014). No research has directly examined the effect of required warmth to conduct a task on the consumer acceptance of AI service, so an accurate estimate of required warmth effect is still missing.

These two research gaps raise important questions: (1) Does consumer acceptance of AI service depend on the extent to which the task requires warmth? (2) Can AI-human collaboration increase consumer acceptance of AI service for tasks that require warmth? We conduct a series of studies to address the following research objectives. First, drawing on social cognition theory and task-technology fit theory, we empirically show that the acceptance of an AI server depends on the warmth a task requires. We also shed light on the underlying process and show that the higher acceptance of AI is driven by the fit between the task and the AI technology. Second, grounded in concept combination theory, we also show that AI-human collaboration can increase the acceptance of an AI server for tasks that require warmth, yet only when a human is clearly in the lead.

Our empirical work makes several contributions to the literature. First, we identify an important task characteristic that determines consumer acceptance of AI service and reveal the negative effect of required warmth on AI acceptance. We also uniquely contribute to the literature by revealing the underlying process that consumers' reluctance to accept AI for tasks requiring high warmth is due to the lack of perceived fit between the task and the AI. Different from extant investigations on the technical suitability/feasibility of AI (e.g., Brynjolfsson & Mitchell, 2017; Brynjolfsson et al., 2018), our focus on perceived fit answers the call by Puntoni, Reczek, Giesler, and Botti (2021) for more empirical studies on how consumers experience AI.

Second, we address the call for further research on the role of AI-human collaboration in consumer acceptance of AI service (Huang & Rust, 2018; Xiao & Kumar, 2021). We are the first to compare several types of AI service: a human laborer working independently, AI supporting a human, AI supervised by a human, and AI working independently. Based on concept combination theory, we theorize how the interplay between required warmth and AI-human collaboration influences consumer acceptance of AI service. The application of concept combination theory into the field of AI-human collaboration offers an important theoretical foundation for subsequent research on consumer acceptance of AI-human collaboration. Our empirical findings further contribute to the literature by showing that AI supporting a human increases the acceptance of AI, as well as for tasks that require high warmth. However, this is not the case for AI supervised by a human.

The remainder of this article is organized into the following sections. First, we introduce the literature review. Then, we propose our hypotheses. Next, we conduct a series of experiments to test the hypotheses. After which we discuss the theoretical and managerial implications, note the limitations of our research, and offer suggestions for future research. Finally, we present our conclusions.

2. Literature review

2.1. Task characteristics and AI acceptance

Scholars have started to examine the effect of task characteristics on AI acceptance. As Table 1 shows, some studies investigated how task characteristics influence employees' acceptance of an AI colleague (e.g., Sampson, 2021; Waytz & Norton, 2014). Some studies took the perspective of the consumer and identified several important task characteristics that explain consumer acceptance of AI service such as social (vs. analytical tasks) in Hertz and Wiese (2019) and subjective (vs. objective) tasks in Castelo et al. (2019). These identified task characteristics are related to, but not identical to, required warmth.

Warmth as one dimension of social cognition refers to the perception of others' positive or negative intent, and captures emotional traits such as caring and friendliness (Fiske et al., 2007; van Doorn et al., 2017). Warmth mainly corresponds to emotional intelligence (Kim et al., 2019; Waytz & Norton, 2014). Recent applications of social cognition theory and the literature on emotional AI or intelligent personal assistants show that when forming attitudes towards and usage intention of AI, people would judge AI's warmth or emotional intelligence (Belanche, Casaló, Schepers, & Flavián, 2021; Čaić, Avelino, Mahr, Odekerken-Schröder, & Bernardino, 2020; Chuah & Yu, 2021; Gelbrich et al., 2021; Hu, Lu, Pan, Gong, & Yang, 2021; Song, Xu, & Zhao, 2022; van Doorn et al., 2017). However, these studies have not considered how consumer acceptance of AI service depends on the extent to which the task requires warmth.

This question becomes more and more prominent and realistic to service managers. Prior studies on emotional AI point out that the rapid technological development will help AI to master emotional skills in the foreseeable future (Huang &, 2021b, 2021c; Huang et al., 2019; Rust & Huang, 2021). AI has already started to provide services for consumers in tasks that require warmth to some degree, such as providing emotional support (Gelbrich et al., 2021), assessing consumer feelings (Sidaoui et al., 2020), caring for aging populations (Turja, Aaltonen, Taipale, & Oksanen, 2020), and building an emotional relationship with people (Song et al., 2022).

Task-technology fit theory provides a theoretical framework for examining how warmth that is required for conducting a task influences the acceptance of AI service. Specifically, task-technology fit theory takes into account task characteristics and states that the fit between technology characteristics and task requirements determines an individual's adoption of the technology (Goodhue & Thompson, 1995). This theory has been employed to explain individuals' acceptance of technology such as mobile business applications in Gebauer and Shaw (2004), although it has been rarely applied to the field of AI acceptance. Accounting for the importance of task characteristics differentiates this theory from the other three popular technology acceptance theories including the Technology Acceptance Model (TAM; Davis, Bagozzi, &

Table 1
Relevant Literature on How Warmth-Related Job/Task Features and AI-Human Collaboration Influence AI Acceptance.

Source	Warmth-related job/task features empirically examined?	What AI-human collaboration empirically examined?		Jobs/tasks × collaboration empirically examined?	Consumer perspective?
	What job/task feature?	AI supporting human?	AI supervised by human?		
Castelo et al. (2019)	Subjective (vs. objective) tasks	No	No	No	Yes
Hertz and Wiese (2019)	Social (vs. analytical) tasks	No	No	No	Yes
Sampson (2021)	Required interpersonal skills to conduct a task	No	No	No	No (worker)
Waytz and Norton (2014)	Emotion-oriented (vs. cognition-oriented) jobs	No	No	No	No (worker)
Longoni et al. (2019)	None	Yes	No	No	Yes
Longoni and Cian (2020)	None	Yes	No	No	Yes
Luo et al. (2021)	None	Yes	No	No	Yes
McLeay et al. (2021)	None	Yes	No	No	Yes
This study	Required warmth to conduct a task	Yes	Yes	Yes	Yes

Warshaw, 1989), the unified theory of acceptance and use of technology (UTAUT; Venkatesh, Thong, & Xu, 2012), and the technology readiness theory (Parasuraman & Colby, 2015; Parasuraman, 2000). TAM, UTAUT, and technology readiness theory have been applied to explain consumer acceptance of AI applications (e.g., Baabdullah, Alalwan, Slade, Raman, & Khatatneh, 2021; Meyer-Waarden & Cloarec, 2021; Pillai, Sivathanu, & Dwivedi, 2020; Prakash & Das, 2021; van Doorn et al., 2017), while these three theories do not consider task characteristics.

2.2. AI-human collaboration

As shown in Table 1, prior studies have noticed the value of AI-human collaboration in service (e.g., Longoni et al., 2019; Longoni & Cian, 2020; Luo et al., 2021; McLeay et al., 2021). Taking Longoni et al. (2019) as an example, they found that consumers show a greater tendency to refuse medical AI for healthcare service when the AI completely replaces a human physician than when there is AI providing a human physician with useful information. These previous studies have not yet examined a situation in which an AI conducts a task under the supervision of a human co-worker, nor considered the interplay between task characteristics and AI-human collaboration.

Originating in the field of cognitive psychology, concept combination theory potentially offers a theoretical framework to explicate how consumers perceive AI-human collaboration. Specifically, concept combination theory explains how people interpret a composite concept/object in terms of its constituents (Gagné & Shoben, 1997; Hampton, 1987; Smith, Osherson, Rips, & Keane, 1988; Wisniewski, 1996). Within concept combination theory, concepts are assumed to consist of slots (which store attributes of the concept) and fillers (the attributes that fill the slots) in a human brain. For example, a server—as a concept—possesses a "warmth" slot that is filled with "low" or "high." Prior business studies have mainly drawn on concept combination theory to address how consumers conceive brand alliances—the combination of two parent brands (Koschmann & Bowman, 2018; Park, Jun, & Shocker, 1996; Swaminathan, Gürhan-Canli, Kubat, & Hayran, 2015). This work has found that the attributes from one or both concepts (i.e., parent brands) can be transferred onto the combination (i.e., brand alliance). The AI-human collaboration also involves two objects: an AI worker and a human worker. Therefore, concept combination theory should predict how consumers react to the composite object (i.e., the whole AI-human collaboration) in terms of its constituents (i.e., the AI worker and the human worker).

3. Hypotheses

3.1. The effect of required warmth on AI acceptance

Warmth captures emotional traits such as caring and understanding others' feelings as well as being friendly (Fiske et al., 2007; van Doorn et al., 2017). Warmth is mainly associated with emotion instead of cognition (Kim et al., 2019; Waytz & Norton, 2014). When the warmth required to conduct a task is high, a satisfactory server for this task needs to therefore be capable of showing feelings or emotions. Although more and more smart objects (e.g., Amazon Alexa) can provide interactions with consumers and revolutionize consumer experience (Hoffman & Novak, 2018), consumers currently still prefer human workers over AI workers when a task involves intensive feelings or emotions. For example, consumers trust human beings more than AI for predicting joke funniness or recommending a romantic partner (Castelo et al., 2019). People also tend to seek advice from humans rather than from robots for identifying emotional states in pictures (Hertz & Wiese, 2019). Following this logic, consumers should also favor human beings over AI for tasks that require high warmth. Therefore, we hypothesize:

H1: Required warmth of a task decreases consumer acceptance of AI service for the task.

The reluctance to accept AI service for a task that requires high warmth possibly can be accounted for by task-technology fit theory. Specifically, human beings are currently believed to master emotion better than objects, including AI (Waytz & Norton, 2014). People generally know that AI is designed and programmed by humans; as such, individuals nowadays believe that AI responses are not driven by AI's true intentions (Kim & Duhachek, 2020). When individuals perceive that AI does not truly understand feelings as humans do, the enjoyment of having emotional interaction with AI can be impaired (Ho et al., 2018). The foregoing discussion thus implies that as the warmth required for conducting a task increases, the fit between the perceived capabilities of AI and task requirements decreases.

Based on task-technology fit theory (Goodhue & Thompson, 1995), the fit between task features and AI characteristics influences an individual's acceptance of AI service. Therefore, as the warmth required for conducting a task increases, the fit between the AI and the task decreases and so the level of consumer acceptance of the AI service for the task is reduced, and we hypothesize the following:

H2: The negative effect of required warmth on consumer acceptance of AI service is mediated by the perceived fit of the AI for the task.

3.2. The moderating role of AI-human collaboration

Using AI-enabled service does not necessarily imply that either only humans serve consumers or only AI serves consumers. Previous literature indicates that AI can collaborate with humans in two main ways. The first one is where AI supports or augments human efforts; specifically, AI plays the role of an assistant or a tool to help a human colleague perform the task (e.g., Longoni et al., 2019; Longoni & Cian, 2020; Luo et al., 2021; McLeay et al., 2021; Wesche & Sonderegger, 2019). The other one is where a human supervises AI; as such, the AI conducts the task but is supervised by a human (e.g., Bansal & Kockelman, 2018; Wang & Lewis, 2007).

We build on concept combination theory to explain how individuals perceive different AI-human collaboration types for tasks varying in required warmth. Given that AI-human collaboration involves the combination of two objects, concept combination theory is a suitable theory that explains consumers' perception of different combinations between humans and AI. People currently believe that human beings are good at emotions (Waytz & Norton, 2014), so warmth should be a salient attribute of human beings. Furthermore, although research in AI extends to tasks that require warmth (Huang & Rust, 2021a, 2021b; Huang et al., 2019), people nowadays still generally believe that humans are better at emotions than AI (Haslam, Kashima, Loughnan, Shi, & Suitner, 2008). Therefore, humans are believed to perform better than AI in terms of warmth.

In this case, a maximum rule applies. In particular, concept combination theory states that if an attribute is salient to any of the constituent concepts, a maximum rule would function as follows: the attribute would be perceived to be salient to the combination of these two concepts (Hampton, 1987; Park et al., 1996). This maximum rule also applies to the performance level of this salient attribute: if either one of the constituent concepts performs well on a salient attribute, the combination of them is also judged to perform well on that attribute (Hampton, 1987; Park et al., 1996). In other words, the maximum rule states that the salience and performance level of an attribute of a combination are consistent with those of the more salient and higher-performing constituent concept (Hampton, 1987; Park et al., 1996). Taking brand alliances as an example, assume that an attribute (e.g., low calorie) is associated with a snack brand but not with its partner brand, so consumers would believe that the composite brand of the two also has low calories (Park et al., 1996). Therefore, given that humans perform better than AI in terms of the salient attribute (warmth), the combination of AI and humans should be perceived to be warmer than AI. For tasks requiring high warmth, AI supporting a human, as a type of AI-human collaboration, would have a higher task-technology fit than AI working independently, resulting in an increased positive consumer attitude towards technology.

For tasks requiring low warmth, the perceived differences in emotional abilities between AI working independently and AI supporting a human should be unimportant. Consequently, the advantage of AI supporting a human vis-a-vis emotion should become negligible, leading to a similar task-technology fit to that of AI working independently. The foregoing discussion thus leads to the following hypothesis:

H3. The effect of required warmth on consumer acceptance of AI service for a task is less negative when AI is supporting humans than when AI is working independently.

Similarly, AI supervised by a human, as another important type of AI-human collaboration, should also have the advantage of being perceived as warmer than AI alone. Therefore, for tasks requiring high warmth, consumers should perceive a higher task-technology fit for AI supervised by a human than AI working independently, resulting in a more positive attitude towards AI service. As to tasks requiring low warmth, the advantage of AI-human collaboration to secure warmth is less critical and should not affect task-technology fit. Thus, we hypothesize:

H4. The effect of required warmth on consumer acceptance of AI service for a task is less negative when AI is supervised by humans than when AI is working independently.

Although, the maximum rule indicates that the salience and performance level of an attribute of a combination match those of the more prominent and superior constituent concept (Hampton, 1987; Park et al., 1996). However, "match" does not mean "equal." Concept combination theory further posits that there is a dominance effect in the match level between a combination and its more salient and higher-performing constituent concept (Hampton, 1988; Park et al., 1996). Actually, the attributes of the dominating concept in the combination would have a stronger impact on individuals' perception of the combination than on the subordinating concept (Hampton, 1988; Park et al., 1996).

In the case of AI supervised by a human, AI automatically performs the task and humans are primed as the supervisors. On the contrary, in the case of AI supporting a human, humans take the lead and AI merely plays an assisting role. Therefore, humans should play a more dominating role like in AI supporting a human rather than AI supervised by a human, so the effects of human attributes on the collaboration should be stronger in the former collaboration type. Considering that individuals perceive humans as more capable of emotion than AI (as per our previous hypotheses), this emotional advantage may be perceived as higher in AI supporting a human than in AI supervised by a human. Therefore, the fit between the perceived warmth of AI supporting a human and task requirements should increase compared to AI supervised by a human. Based on task-technology fit theory, the fit determines consumer attitude towards technology. Thus, we posit the following hypothesis:

H5. The effect of required warmth on consumer acceptance of AI service for a task is less negative when AI supports a human colleague than when AI is supervised by a human.

4. Research design

We test our hypotheses in a series of four choice-based conjoint (CBC) experiments and one survey (see Table 2). Study 1a is a CBC experiment that provides an initial examination of how required warmth influences consumer acceptance of AI service in the education industry. Then, based on a survey in the education industry, Study 1b does not only replicate the main effect of required warmth on AI acceptance identified in Study 1a, but also examines the mediating role of task-AI fit.

Studies 2a-2c investigate the moderating role of AI-human collaboration. Different from Studies 1a-1b, Studies 2a-2c provide four service provision options to consumers: task conducted exclusively by a human worker, exclusively by AI, mainly by a human worker who is supported by AI, or mainly by AI that is supervised by a human worker. To ensure the robustness of the findings, we replicate the same CBC experiment design in several service industries that are undergoing the transformation of AI including education, journalism, and transportation.

5. Study 1: the effect of required warmth on AI acceptance

Study 1 investigated how the required warmth to conduct a task determines consumer acceptance of AI service. In Study 1a, we focused on the main effect of required warmth on AI acceptance. We then conducted Study 1b to examine the mediating effect of task-AI fit.

5.1. Study 1a: The main effect of required warmth on AI acceptance

In the experiment, we focused on the education industry, which is undergoing AI-driven transformation. For example, some schools have employed AI-powered systems or robots to substitute human teachers for several tasks, such as giving lessons (Reuters, 2018) and grading essays (Chen, 2018).

5.1.1. Method

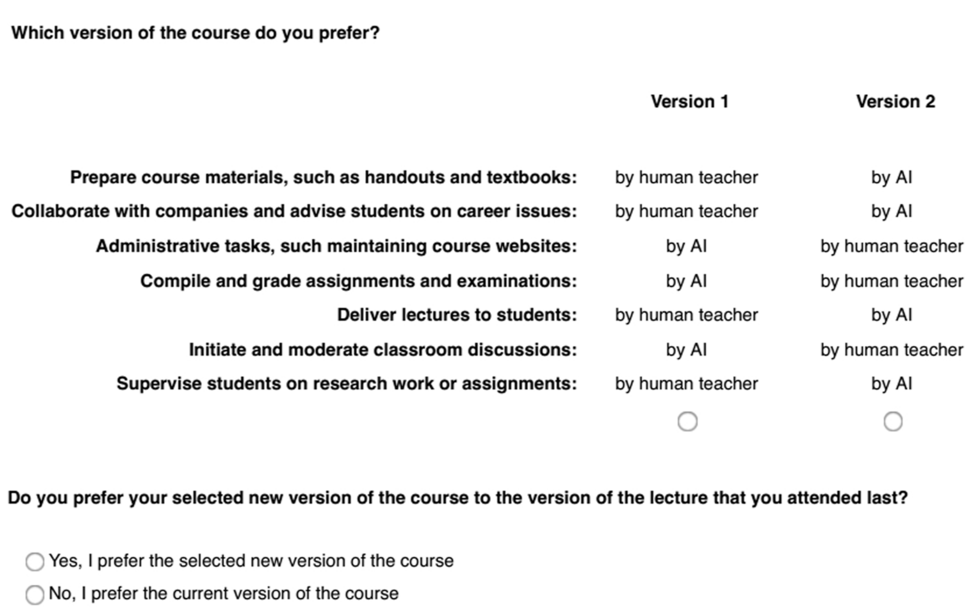
Participants and design. A total of 234 voluntary students from a large European university (M_{age} = 20.6 years, 37.6% female) participated in the lab experiment for money or school credit compensation. We employed a choice-based conjoint experiment. The format of the

Table 2
Research Designs of Studies.

Features	Study 1a	Study 1b	Study 2a	Study 2b	Study 2c
Industry	Education	Education	Education	Journalism	Transportation
Method	Choice-based conjoint lab experiment	Online survey	Choice-based conjoint lab experiment	Choice-based conjoint lab experiment	Choice-based conjoint online experiment
Server type (attribute level)	• By AI human • By human teacher	Same as Study 1a	• By human teacher • By AI teacher • Mainly by human professor who is supported by AI • Mainly by AI that is supervised by a human teacher	• By human writer • By AI writer • Mainly by human writer who is supported by AI • Mainly by AI that is supervised by a human writer	• By human driver • By AI driver • Mainly by human driver who is supported by AI • Mainly by AI that is supervised by a human driver
Main tasks (attributes)	• Prepare course materials, such as handouts and textbooks. • Collaborate with companies and advise students on career issues. • Perform administrative tasks, such as maintaining course websites. • Compile and grade assignments and examinations. • Deliver lectures to students. • Initiate and moderate classroom discussions. • Supervise students on research work or assignments.	Same as Study 1a	Same as Study 1a	• Conduct research to obtain factual information using sources such as newspapers, diaries, and interviews. • Write short stories, biographies, articles, or descriptive or critical analyses. • Prepare works in appropriate format for publication, and send them to publishers • Confer with editors or publishers to discuss changes or revisions to written material. • Revise written material to satisfy needs of publishers. • Collaborate with other writers on specific projects. • Follow appropriate procedures to get copyrights for completed work.	• Communicate with dispatchers to receive requests for passenger service. • Determine fares based on trip distances and times and announce fares to passengers. • Pick up passengers at prearranged locations. • Ensure that passengers follow safety regulations according to state laws governing vehicle operation. • Drive taxicabs to transport passengers to prearranged locations. • Provide passengers with information about the local area and points of interest or give advice on hotels and restaurants. • Collect fares or vouchers from passengers and make change or issue receipts, as necessary.
Estimation model	Multinomial logit model	Linear regression model	Multinomial logit model	Multinomial logit model	Multinomial logit model
Sample	234 students in the Netherlands	234 students in the U.K.	218 students in the Netherlands	141 students in the Netherlands	204 individuals in the U.K.

experiment is summarized in Table 2. In particular, following prior studies (Huang et al., 2019; Sampson, 2021), we first chose tasks for this experiment from the O*NET database which is a job database generated and updated by the U.S. Department of Labor. The selected tasks contain 1) preparation of course materials, 2) career advice, 3) administrative tasks, 4) examinations, 5) lecturing, 6) classroom discussions, and 7) student supervision (see Web Appendix A for more details). Each of the tasks constituted an attribute in the conjoint experiment for which we considered two levels: the task was performed by a human teacher or by an AI teacher. We generated multiple versions of fictitious courses based on random combinations of the attribute levels across the seven tasks (e.g., a course in which a human teacher performed the lecturing, an AI was responsible for the examinations).

Procedure and measures. Before the conjoint section started, we listed some existing examples of AI teaching, such as robots as teaching assistants to manage a lesson and show that AI has the potential to replace


Which version of the course do you prefer?

	Version 1	Version 2
Prepare course materials, such as handouts and textbooks:	by human teacher	by AI
Collaborate with companies and advise students on career issues:	by human teacher	by AI
Administrative tasks, such maintaining course websites:	by AI	by human teacher
Compile and grade assignments and examinations:	by AI	by human teacher
Deliver lectures to students:	by human teacher	by AI
Initiate and moderate classroom discussions:	by AI	by human teacher
Supervise students on research work or assignments:	by human teacher	by AI

Do you prefer your selected new version of the course to the version of the lecture that you attended last?

Yes, I prefer the selected new version of the course
No, I prefer the current version of the course

Fig. 1. An Exemplary Choice Set in Study 1a.

human teachers. We then had participants think about a course that they liked most from the courses they took in the last teaching block and imagine that the course would be re-designed in the next academic year. We then showed participants different versions of how this course might be changed by including AI according to the experimental design. For example, Versions 1 and 2 in Fig. 1 showed different course designs by altering the teacher type for each task. We subsequently asked students to indicate their most preferred form of teaching from multiple alternative course versions.

After the conjoint section, participants rated required warmth ("I feel the human/AI teacher responsible for this task needs to understand my feelings," ". be well intentioned," and ". be friendly"; Cronbach's alpha =0.681; Čaić et al., 2020) and required competence ("I feel the human/AI teacher responsible for this task needs to be competent," ".be reliable," and ".be knowledgeable;" Cronbach's alpha =0.685) for each task on a five-point scale. Competence is the second social cognition dimension besides warmth and captures traits like being skillful and efficacious (Fiske et al., 2007; van Doorn et al., 2017). Correspondingly, required competence refers to the extent to which the agent of a task needs to be competent and functioned as a control variable in the estimation model to avoid a possible confounding effect.

5.1.2. Results

Table 3 shows evidence that there was a large variation in the required warmth with administrative tasks rated the lowest (2.47) and career advice the highest (4.23). We estimated consumer preference using a mixed logit model within a hierarchical Bayes procedure (Web Appendix B). We started with a base model in which we did not account for the effects of required warmth and competence but only modeled consumer acceptance of AI for each of the tasks (Model 1, Table 4). The task-specific intercepts refer to students' acceptance of an AI teacher for that task. The "none" option parameter, which represented the current mode of teaching, is negative. Thus, only if a combined score across tasks exhibited a more negative score than the "none" option, students would then likely reject the new course. As shown in Table 4, some teaching tasks (e.g., preparing course material, performing administrative tasks) have higher estimated intercepts than others (e.g., delivering lectures and managing discussions), indicating that students on average are more willing to accept AI for the former tasks. Considering that the former tasks require relatively less warmth than the others (see Table 3), the preliminary results support that required warmth decreases consumer acceptance of AI.

Model 2 in Table 4 extended the base model by the marginal effects of required warmth and competence, depending on the respondent-specific perception of required warmth and competence (see Table 3; we mean-centered the values for the estimation). The results showed that consistent with H1, required warmth significantly reduced

Table 4
Estimation Results in Study 1a.

Variable	Model 1	Model 2
Hypothesized Effect		
Required warmth		-0.070^{**}
		(.024)
Controls		
Required competence		-0.077*
		(.051)
Task-specific Intercepts		
Prepare course material	-0.144^{**}	-0.143^{**}
	(.031)	(.036)
Advise on career issues	-0.880^{***}	-0.876^{***}
	(.000)	(.000)
Administrative tasks	$.142^{**}$	$.141^{**}$
	(.025)	(.031)
Compile and grade exams	-0.290^{***}	-0.289^{***}
	(.001)	(.000)
Deliver lectures	-1.991^{***}	-1.985^{***}
	(.000)	(.000)
Manage discussion	-1.402^{***}	-1.397^{***}
	(.000)	(.000)
Supervise students	-0.955^{***}	-0.952^{***}
	(.000)	(.000)
None Option	-0.705^{***}	-0.700^{***}
	(.000)	(.000)

Notes: The p-value in the parentheses refers to the posterior probability that a parameter is larger/smaller than 0. * $p < .1$; ** $p < .05$; *** $p < .01$.

consumer acceptance of an AI teacher ($\lambda = -0.070$, $p = .024$). Required competence also had a marginally significant negative effect on consumer acceptance of an AI teacher ($\lambda = -0.077$, $p = .051$). The comparison between Model 1 and Model 2 showed the robustness of the effect of required warmth on AI acceptance. The negligible differences in the estimated task-specific intercepts between Model 1 and Model 2 were due to centering required warmth and required competence.

5.2. Study 1b: The mediating role of task-AI fit

Study 1b investigated whether task-AI fit mediates the effect of the required warmth to conduct a task on consumer acceptance of AI.

5.2.1. Method

Participants and design. A total of 252 voluntary respondents in the U.K. participated in an online survey on Prolific with monetary rewards. Excluding 18 non-student respondents, the final sample consisted of 234 students (M_{age} = 24.3 years; 106 female, 122 male, 6 did not disclose). We focused on the education industry and adopted the same seven teaching tasks as stimuli as we did in Study 1a.

Procedure and measures. We asked for demographics before the

Table 3
The Means (SDs) of the Required Warmth in Studies.

Studies in Education				Study 2b in Journalism		Study 2c in Transportation	
Tasks	Study 1a: Warmth	Study 1b: Warmth	Study 2a: Warmth	Tasks	Warmth	Tasks	Warmth
Prepare course material	3.17 (0.98)	3.74 (0.78)	3.20 (0.90)	Conduct research	3.56 (0.86)	Communicate with dispatchers	3.51 (1.04)
Advise on career issues	4.23 (0.60)	4.08 (0.75)	4.13 (0.65)	Write stories	4.00 (0.76)	Determine fares	3.30 (0.99)
Perform administrative tasks	2.47 (0.95)	3.38 (0.89)	2.62 (0.98)	Prepare works	2.77 (1.03)	Pick up passengers	3.66 (1.01)
Compile and grade exams	2.98 (1.00)	3.54 (0.91)	3.09 (0.89)	Confer with editors	4.08 (0.72)	Ensure passengers to follow rules	3.66 (0.96)
Deliver lectures	3.82 (0.87)	4.11 (0.96)	3.94 (0.75)	Revise materials	3.71 (0.90)	Transport passengers	3.70 (1.04)
Manage discussion	4.05 (0.70)	3.88 (0.75)	4.02 (0.72)	Collaborate with others	4.46 (0.64)	Provide info	4.23 (0.81)
Supervise students	3.95 (0.76)	4.18 (0.70)	3.97 (0.81)	Follow procedures	2.67 (1.03)	Collect fares	3.36 (1.05)

survey started, including student status, age, and gender. We then introduced the same existing examples of AI teaching as in Study 1a. We randomly presented one of the seven tasks to participants and had them imagine that their university was considering replacing human teachers with AI teachers to perform that task. Participants then rated required warmth (Cronbach's alpha =.733) and required competence (Cronbach's alpha =.815) using the same scales as in Study 1a. Afterwards, participants rated their understanding of AI for the task ("I understand the use of AI for this task"). We added AI understanding into the estimation model as a control because individual differences in understanding AI could maybe influence what they think about AI service. We did not do so in the choice-based conjoint experiments because we accepted a mixed logit model within a hierarchical Bayes procedure that estimates individual-level utility and thus controls for individual heterogeneity including the differences in AI understanding. Subsequently, using the eight-item scale from Lin and Huang (2008), participants assessed perceived task-AI fit ("An AI teacher is adequate/appropriate/useful to perform this task," "An AI teacher is very compatible with this task," "An AI teacher is helpful/sufficient for this task," "An AI teacher makes the task very easy," and "In general, an AI teacher fits well with this task;" Cronbach's alpha =0.953). Finally, participants indicated their acceptance of AI teachers on a four-item scale ("An AI teacher for this task is a good/wise idea," "An AI teacher is favorable to this task," "Overall, I like the idea of an AI teacher being responsible for this task"; Cronbach's alpha =0.953; Bhattacherjee & Sanford, 2006). All the variables were measured on a five-point scale from 1 ("totally disagree") to 5 ("totally agree").

5.2.2. Results

Table 3 reflects that required warmth varied across tasks. Supervising students required the highest warmth (M = 4.18), followed by delivering lectures (M = 4.11), advising on career issues (M = 4.08), managing discussions (M = 3.88), preparing course material (M = 3.74), compiling and grading exams (M = 3.54), and conducting administrative tasks (M = 3.38). Participants had a high level of understanding AI for all these tasks with the average value of 4.03, the minimum value of 3.71 (for advising on career issues), and the maximum value of 4.38 (for compiling and grading exams). Following the approach adopted by Castelo et al. (2019), we conducted a mediation analysis using PROCESS to examine whether task-AI fit mediated the relationship between the measure of required warmth and AI acceptance (Model 4 in Hayes, 2017). The results in Table 5 showed a significant negative effect of required warmth on AI acceptance ($\lambda = -0.481$, $p = .000$, Model 2; in support of H1), as well as a significant negative effect of required warmth on task-AI fit ($\lambda = -0.477$, $p = .000$, Model 1). The path analysis demonstrated the expected mediational path (required warmth → decreased task-AI fit → decreased AI acceptance) at the 95% confidence interval (CI) (indirect effect = −0.463, 95% CI: −0.598, −0.322). Furthermore, the mediator rendered the direct effect non-significant ($\lambda = -0.018$, $p = .720$, Model 3). Thus, this suggested full mediation through task-AI fit, supporting H2. In this mediation analysis, we also controlled for required competence which has a direct negative effect ($\lambda = -0.164$, $p = .010$, Model 3) and AI understanding ($\lambda = 0.043$, $p = .268$, Model 3).

Table 5
Estimation Results in Study 1b.

Independent variables	Dependent variables		
	Task-AI fit	AI acceptance	
	Model 1	Model 2	Model 3
Control paths			
Required competence	.111 (.269)	-.056 (.628)	-.164 (.010)**
AI understanding	.270 (.000)***	.305 (.000)***	.043 (.268)
Direct effect paths			
Required warmth	-.477 (.000)***	-.481 (.000)***	-.018 (.720)
Task-AI fit			.970 (.000)***
Indirect effect of required warmth	Estimate	95% confidence interval (CI)	
	-.463	(-.598, -.322)	

Notes: The p-value in the parentheses. * p <.1; ** p <.05; *** p <.01.

6. Study 2: the moderating role of AI-human collaboration

Study 2 examined the effect of the required warmth to conduct a task on consumer acceptance of AI service for different types of AI-human collaborations. In Study 2, to check the robustness of the results and the external validity of the conclusions, we replicated the same investigation across different focal industries including education, journalism, and transportation. A number of famous media institutions, such as The New York Times, Washington Post, and Reuters, have already been using AI to generate content (Marr, 2019). Multiple traditional car and high-tech companies have invested large amounts of resources in producing self-driving vehicles using AI, such as Waymo by Alphabet, Apollo by Baidu, and Cruise by GM. The potential market for self-driving vehicles is considerable as attested to by Waymo's valuation of more than $30 billion (Waters, 2020).

6.1. Method

Study 2a: AI-human collaboration in education. In Study 2a, 218 voluntary university students (M_{age} = 20.17 years, 34.9% female) took part in a lab experiment in exchange for money or school credit. Study 2a used the same conjoint experiment as Study 1a, with the exception that it provided four service options to consumers: task conducted exclusively by a human worker, exclusively by AI, mainly by a human worker who is supported by AI, or mainly by AI that is supervised by a human worker. Consistent with Study 1a, the option "task conducted exclusively by a human worker" functions as a reference group.

Study 2b: AI-human collaboration in journalism. In Study 2b, 141 university student volunteers (M_{age} = 20.96 years, 70.2% female) attended the lab experiment for either money or school credit. Study 2b adopted the same conjoint experiment as Study 2a, except for the task stimuli that were selected in a similar way in Study 1a as Study 2b focused on journalism (see Table 2; details in Web Appendix C).

Study 2c: AI-human collaboration in transportation service. In Study 2c, 204 volunteers (52.5% female) participated in an online experiment on Prolific for monetary rewards. Study 2c used the same methodology as Study 2a except Study 2c focused on transportation (see Table 2; details in Web Appendix D).

6.2. Results

We averaged the scale items to form measures for required warmth ($\alpha = 0.664/.748/.742$) and required competence ($\alpha = 0.720/.790/.761$) in Study 2a/2b/2c. Table 3 shows the variations of required warmth across the tasks. We estimated consumer preference using the same model as Study 1a except each attribute has four levels (i.e., four service options; Web Appendix B). As shown in Table 6, H1 received support in Study 2a/2b/2c: the required warmth to conduct a task significantly reduced consumer acceptance of AI service when AI worked independently ($\lambda = -0.133/-0.249/-0.150$, $p = .004/.000/.001$). Corroborating H3 in Study 2a/2b/2c, the negative effect of required warmth in the case of only AI ($\lambda = -0.133/-0.249/-0.150$) was stronger than in the case of AI supporting a human ($\lambda = -0.001/-0.102/-0.063$; $\Delta\lambda = -0.132/-0.147/-0.087$, $p = .006/.005/.032$). Yet, in Study 2a/2b/2c, required warmth unexpectedly exerted an equally negative effect on the acceptance of AI service when the task is conducted by AI but supervised by a human ($\lambda = -0.116/-0.178/-0.126$), and AI only ($\lambda = -0.133/-0.249/-0.150$; $\Delta\lambda = -0.017/$

Table 6
Estimation Results in Studies 2a-2c.

Variable	Study 2a	Study 2b	Study 2c
Hypothesized Effects			
Required warmth			
AI	-0.133***	-0.249***	-0.150***
	(.004)	(.000)	(.001)
Human supported by AI	-0.001	-0.102**	-0.063*
	(.493)	(.013)	(.069)
AI supervised by human	-0.116***	-0.178***	-0.126***
	(.003)	(.000)	(.002)
Controls			
Required competence			
AI	-0.184***	-0.032	.040
	(.002)	(.321)	(.287)
Human supported by AI	.068*	-0.049	-0.014
	(.095)	(.200)	(.417)
AI supervised by human	-0.014	-0.066	.011
	(.397)	(.166)	(.431)

Notes: The p-value in the parentheses refers to the posterior probability that a parameter is larger/smaller than 0. Controls, including task-specific intercepts and non-option, are omitted in this table and shown in Web Appendix E. * $p < .1$; ** $p < .05$; *** $p < .01$.

$-0.071/-0.024$, $p = .378/.115/.302$), thus not supporting H4. As expected in H5, required warmth in the case of AI supervised by a human ($\lambda = -0.116/-0.178/-0.126$) had a stronger negative effect than in the case of AI supporting a human ($\lambda = -0.001/-0.102/-0.063$; $\Delta\lambda = -0.115/-0.076/-0.063, p = .010/.085/.091$) in Study 2a/2b/2c, although the difference was marginal in Study 2b/2c. Moreover, the results of Study 2a showed that required competence also significantly reduced consumer acceptance of AI service when AI worked independently ($\lambda = -0.184$, $p = .002$), which was consistent with Study 1a.

7. Discussion

Our research yields important insights into the impact of required warmth on AI acceptance and the moderating role of AI-human collaboration. Table 7 provides an overview of our key findings.

First, in support of H1, Study 1a shows that required warmth to conduct a task negatively influences consumer acceptance of AI service for the task, which was replicated in the subsequent Studies 1b and 2a-2c. This finding is consistent with the results of prior research on social cognition theory, where warmth can influence consumer acceptance of intelligent personal assistants (Gelbrich et al., 2021; Hu et al., 2021), chatbots for service failure recovery (Huang, Gursoy, Zhang, Nunkoo, & Shi, 2021), a robotic chef (Zhu & Chang, 2020), robots in frontline service (van Doorn et al., 2017), and a robotic coach for games (Čaić et al., 2020). Given that warmth mainly corresponds to emotional intelligence, our results are also in line with the literature in emotional AI by indicating the importance of emotional intelligence in AI acceptance. For example, Song et al. (2022) find that emotional capabilities of intelligent assistants can influence consumer commitment and usage intention.

Study 1b reveals that consumers are not willing to accept AI for tasks that require high warmth due to the low fit between AI and the task at hand, confirming H2. In line with task-technology fit theory (Goodhue & Thompson, 1995) and its prior applications (e.g., explaining user acceptance of mobile business applications in Gebauer & Shaw, 2004), the fit between task requirement (e.g., required warmth) and technology (e.g., AI) fully mediates the effect of required warmth on AI acceptance and thus explains why required warmth can influence consumer acceptance of AI service.

Studies 2a-2c consistently show that for tasks that require high warmth, the AI-human collaboration where AI supports a human can increase AI acceptance (corroborating H3), while AI being supervised by a human cannot do so (not supporting H4). These results partially confirm concept combination theory that the value of an attribute (i.e., warmth) of a combination (e.g., AI-human collaboration) is consistent with the more salient and higher-performing constituent concept (e.g., human beings) (Hampton, 1987; Park et al., 1996). Yet, surprisingly, countering our expectations in H4 no significant difference exists between consumer perceptions of AI working independently and AI supervised by a human. This phenomenon may be explained by the role of the human probably seen as too limited when only supervising the AI. Then, the difference between AI working independently and AI supervised by a human may seem negligible.

Studies 2a-2c also reveal that as expected in H5, required warmth in the case of AI supervised by a human has a stronger negative effect than in the case of AI supporting a human. Reversely, AI supporting a human plays a more important role in compensating for the negative effect of required warmth on AI acceptance. This finding is in line with concept combination theory (Hampton, 1988; Park et al., 1996) that states that the attributes of the dominating concept (e.g., human beings in AI supporting a human) in the combination have a stronger effect on individuals' perception of the combination than on the subordinating concept (e.g., AI in AI supporting a human).

The results in Studies 2a-2c are also in line with prior research on AI-human collaboration. Specifically, the findings support the argument that AI is suitable to replace human beings for some tasks but at least now not for all types of tasks (Coombs, 2020; Dwivedi, Hughes et al., 2021; Huang & Rust, 2021b; Huang et al., 2019; Seeber et al., 2020). AI that interacts with and works with human labor would create more business values (Zhang, Pee, & Cui, 2021), make better decisions (Duan et al., 2019; Fügener, Grahl, Gupta, & Ketter, 2021; Jussupow, Spohrer, Heinzl, & Gawlitza, 2021), and advance product design (Liao, Hansen, & Chai, 2020).

Table 7
Main Findings in Studies.

Hypothesis	Studies	Result	Findings
H1	Studies 1a, 1b, 2a-2c	Supported	Required warmth of a task decreases consumer acceptance of AI service for the task.
H2	Study 1b	Supported	The perceived fit of AI for the task mediates the negative effect of required warmth on AI acceptance.
H3	Studies 2a-2c	Supported	An AI-human collaboration where AI supports a human employee can increase consumer acceptance of AI also for tasks that require high warmth.
H4	Studies 2a-2c	Not supported	An AI-human collaboration where AI is supervised by a human employee can NOT increase consumer acceptance of AI also for tasks that require high warmth.
H5	Studies 2a-2c	Supported	Faced with a task that requires high warmth, consumers are more willing to accept the collaboration of AI supporting humans than the collaboration of AI being supervised by humans.

7.1. Theoretical contributions and implications

This research makes the following theoretical contributions. First, little literature has examined how required warmth to conduct a task influences AI acceptance. We reveal that required warmth is an important task characteristic that can explain varying consumer acceptance of AI service across tasks. A series of studies empirically show that required warmth negatively influences AI acceptance. This finding means that the required warmth can indicate what tasks AI is suitable to perform from the consumer perspective.

Second, drawing on task-technology fit theory, our research sheds light on the underlying process. We find that the extent to which AI fits the needed warmth to conduct the task mediates the relationship between required warmth and consumer acceptance of AI service. Compared to the extant work on the technical suitability/feasibility of AI (e.g., Brynjolfsson & Mitchell, 2017; Brynjolfsson et al., 2018), this finding on perceived fit by consumers answers Puntoni et al. (2021) call for further examination of AI from the consumer experience perspective rather than the technology itself.

Third, based on concept combination theory, we theorize and empirically test how AI-human collaboration influences consumer acceptance of AI service, depending on the warmth a task requires. We use two types of AI-human collaboration that already exist in practice: AI supporting a human—where the human remains in the lead and AI only plays a supporting role (e.g., Longoni et al., 2019; Longoni & Cian, 2020)—and AI supervised by a human—where AI has the main role in conducting a task and the human only functions as a supervisor (e.g., Bansal & Kockelman, 2018; Wang & Lewis, 2007). We distinctly contribute to the literature by showing that framing the collaboration as AI supporting a human employee can increase acceptance of AI involvement even for tasks that require high warmth. This work answers the call for further empirical insights on AI-human collaboration in consumer acceptance of AI service (Huang & Rust, 2018; Xiao & Kumar, 2021). Moreover, our introduction of concept combination theory into the field of AI-human collaboration provides an important theoretical foundation for subsequent investigations on how consumers perceive AI-human collaboration.

7.2. Implications for practice

The use of AI in service is markedly increasing (Davenport et al., 2020; Gursoy, Chi, Lu, & Nunkoo, 2019; Jörling, Böhm, & Paluch, 2019; Sung, Bae, Han, & Kwon, 2021; Tofangchi, Hanelt, Marz, & Kolbe, 2021). The global AI market size reached \$39.9 billion in 2019 and is predicted to rise at a compound annual growth rate of 42.2% from 2020 to 2027 (GrandViewResearch, 2020). However, consumers do not accept all AI applications in the service industry (Ostrom, Fotheringham, & Bitner, 2019). Against this backdrop, our work offers several important practical insights.

First, because consumer acceptance of AI service varies across tasks, AI replacement should occur at the task level rather than the job level. Our findings suggest that service managers should pay close attention to the critical role of required warmth when considering consumer acceptance of the AI service. The required warmth to conduct a task particularly undermines consumer acceptance of AI service. Therefore, from a consumer perspective, not all tasks are suitable for AI. For those requiring high warmth, companies should assign employees to serve consumers. In contrast, consumers are amenable to AI agents which do tasks that do not require high warmth. Accordingly, companies that adopt AI should be mindful of whether introducing AI employees is compatible with the service they offer in terms of required warmth.

Second, advancement in AI is increasingly enabling and encouraging service providers to replace human employees with AI, thus threatening human jobs. Employees feel discomfort and stress (Granulo et al., 2019; Waytz & Norton, 2014). The negative effect of required warmth on AI acceptance also provides suggestions for employees. In particular, currently, consumers are still less willing to accept AI than human workers for tasks that require high warmth. Therefore, to avoid AI replacement and increase competitiveness in the job market, service employees should realize the importance of emotional intelligence and develop their emotional abilities such as understanding consumers' feelings, empathizing with clients, and building an emotional connection. Reversely, managers could enhance productivity and employees' satisfaction by offering training programs on emotional intelligence and relationship building.

Third, our findings show that consumers tend to refuse AI service for tasks that require high warmth due to the low perceived fit between the AI and the task at hand. This result suggests that managers should not only consider the technical suitability of AI to tasks but also care about how consumers perceive the fit between AI and tasks. Technical suitability does not equal perceived fit by consumers. Ignoring consumers' actual experiences and feelings deters consumer acceptance of AI service. It is necessary for managers to invite some consumers to test consumer perceived fit between the AI and the service provided.

Fourth, service providers should recognize that for tasks that require high warmth, the collaboration between AI and employees can increase consumers' willingness to accept the AI service. AI service does not necessarily imply that either only humans serve consumers or only AI serves consumers. On the one hand, AI could support a human colleague in performing the task. For example, in self-driving, AI provides assisted functions—such as stay-in-lane assistance—but the human driver takes the lead to control the vehicle (NHTSA, 2017). On the other hand, AI might conduct the task but is supervised by a human. Taking self-driving as an example, AI performs all driving functions and the human driver would only need to monitor such functions (NHTSA, 2017). Our results indicate that if companies still want to introduce AI to perform tasks requiring high warmth, they are advised to opt for a collaboration in which AI supports a human; specifically, putting the human clearly in charge and AI in an assisting role. However, the collaboration of AI as being supervised by a human employee will not make consumers more accepting of AI service for tasks that require high warmth.

Fifth, our work also offers managers an example of how to utilize choice-based conjoint (CBC) experiments for designing AI service. Managers can take the following main steps: (1) either summarize the core tasks within the service on their own or refer to the O*NET database; (2) be familiar with AI's functions and discuss with employees to come up with possible types of AI-human collaboration; and (3) create and implement the CBC experiment by using the tasks identified in step 1 as attributes and the collaboration forms in step 2 as levels for each attribute.

7.3. Limitations and future research direction

The limitations of our work provide some direction for future research. First, our studies relied on informants' self-reported attitudes rather than real behavior. Replicating the identified effects in field settings to improve the external validity of our findings would be valuable. Using field settings would improve participants' understanding of what AI service is and how AI collaborates with humans in actual life. Such enhanced comprehension understanding could lead to the revelation of consumers' likely reactions to AI service. Researchers will have opportunities to fill this gap when more AI service is launched into the market.

Second, we focused on the warmth dimension of social cognition theory and only considered required competence as a control variable. However, we found that required competence can negatively influence consumer acceptance of AI service for teaching tasks but not for writing or driving tasks. This is perhaps because the competence dimension can be decomposed into cognitive abilities containing analytical reasoning and problem-solving ability (Waytz & Norton, 2014). These capacities correspond to analytical intelligence and intuitive intelligence (Huang & Rust, 2018). Individuals trust algorithms more than human beings for some analytical tasks, such as analyzing data and giving directions (Castelo et al., 2019). In contrast, intuitive intelligence encompasses creative thinking and adaptivity to new situations (Huang & Rust, 2018). AI is recently developing to perform more creative tasks such as the famous Go player AlphaGo and is predicted to mimic intuitive intelligence well in the near future (Huang & Rust, 2018). However, research shows that consumers currently still consider AI less capable of high-level construal abilities (deep understanding of new situations) than human beings (Kim & Duhachek, 2020). Consequently, the effect of required competence on consumer acceptance of AI service may depend on which type of intelligence a task requires. For example, participants in our studies may have believed that teaching tasks to a larger extent demands intuitive intelligence rather than analytical intelligence, thus leading to a negative effect of required competence on consumer acceptance of the AI service. Further research can explore the following questions: Do required analytical and intuitive intelligence have different effects on consumer acceptance of AI service? If so, when assessing required competence to conduct a task, how do consumers assign importance to the required analytical and intuitive intelligence?

Third, inconsistent with our expectation, there was no significant difference in consumer perceptions of AI working independently and AI supervised by a human. This unanticipated result leaves room for further investigation on the degree to which humans engage in collaboration with AI. Future empirical work could explore how the role of employees in AI-human collaboration can be made sufficiently salient to consumers and foster acceptance of AI service. Moreover, when examining the effect of interplay between AI-human collaboration types and required warmth on AI acceptance, we did not empirically test whether task-AI fit mediates the effect of interplay on AI acceptance. Further research could do so.

Fourth, our findings are based on the current status of AI. Currently, AI can automatically perform routine tasks and process information for problem-solving and learn from it (Huang & Rust, 2018). What is more, some AI applications (e.g., Google's DeepMind AlphaGo) can, to some degree, think creatively (Huang & Rust, 2018). However, it is still quite challenging for AI to recognize and understand others' feelings (Huang & Rust, 2018). Therefore, individuals generally believe that AI does not truly understand others' feelings (Ho et al., 2018). We thus found a negative effect of required warmth on consumer acceptance of AI service. Yet with the development of AI, it could become good at tasks that require warmth within the following decades and eventually replace human workers for those tasks (Huang & Rust, 2018; Huang et al., 2019; Rust & Huang, 2021). In light of this, the way AI service is currently perceived may possibly change over time. Accordingly, researchers should revise and update our findings in the future.

8. Conclusion

Our study examines how required warmth influences consumer acceptance of AI service and how AI-human collaboration plays a moderating role. Grounded in social cognition theory, we proposed required warmth to characterize service tasks. Drawing on task-technology fit theory, we theorized and empirically found that consumers refuse AI for tasks that require high warmth due to the low fit between the AI and the task at hand. Based on concept combination theory, we compared several types of AI service: a human laborer working independently, AI supporting a human, AI supervised by a human, and AI working independently. The empirical results revealed that AI supporting a human increases the acceptance of AI for tasks that require high warmth. However, this is not the case for AI supervised by a human. In obtaining these outcomes, we extend the theoretical understanding of the impact of required warmth on consumer acceptance of AI service as well as the moderating role of AI-human collaboration. We encourage managers to be aware that acceptance of AI differs between different tasks, and that consumers are reluctant to accept AI for tasks that require high warmth. If managers wish to use AI (also for tasks that require high warmth), they should opt for a collaboration between AI and employees, and they should frame this cooperation as AI supporting their staff.

CRediT authorship contribution statement

Chenming Peng: Conceptualization, Methodology, Writing – original draft. **Jenny van Doorn:** Supervision, Conceptualization, Writing – review & editing. **Felix Eggers:** Supervision, Methodology, Writing – review & editing. **Jaap E. Wieringa:** Supervision, Methodology, Writing – review & editing.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ijinfomgt.2022.102533.

References

Autor, D. H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review, 103*(5), 1553–1597.

Baabdullah, A. M., Alalwan, A. A., Slade, E. L., Raman, R., & Khatatneh, K. F. (2021). SMEs and artificial intelligence (AI): Antecedents and consequences of AI-based B2B practices. *Industrial Marketing Management, 98*, 255–270.

Bansal, P., & Kockelman, K. M. (2018). Are we ready to embrace connected and self-driving vehicles? A case study of Texans. *Transportation, 45*(2), 641–675.

Belanche, D., Casaló, L. V., Schepers, J., & Flavián, C. (2021). Examining the effects of robots' physical appearance, warmth, and competence in frontline services: The Humanness-Value-Loyalty model. *Psychology & Marketing, 38*(12), 2357–2376.

Bhattacherjee, A., & Sanford, C. (2006). Influence processes for information technology acceptance: An elaboration likelihood model. *MIS Quarterly*, 805–825.

Borges, A. F., Laurindo, F. J., Spínola, M. M., Gonçalves, R. F., & Mattos, C. A. (2021). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. *International Journal of Information Management, 57*, Article 102225.

Brynjolfsson, E., & Mitchell, T. (2017). What can machine learning do? Workforce implications. *Science, 358*(6370), 1530–1534.

Brynjolfsson, E., Mitchell, T., & Rock, D. (2018). What can machines learn, and what does it mean for occupations and the economy? In *AEA Papers and Proceedings* (Vol. 108, pp. 43–47).

Čaić, M., Avelino, J., Mahr, D., Odekerken-Schröder, G., & Bernardino, A. (2020). Robotic versus human coaches for active aging: An automated social presence perspective. *International Journal of Social Robotics, 12*(4), 867–882.

Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-dependent algorithm aversion. *Journal of Marketing Research, 56*(5), 809–825.

Chen, S. (2018). China's Schools Are Quietly Using AI to Mark Students' Essays. But Do the Robots Make the Grade? Retrieved July 25, 2020 from 〈https://www.scmp.com/news/china/society/article/2147833/chinas-schools-are-quietly-using-ai-mark-students-essays-do〉.

Chuah, S. H.-W., & Yu, J. (2021). The future of service: The power of emotion in human-robot interaction. *Journal of Retailing and Consumer Services, 61*, Article 102551.

Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. *International Journal of Information Management, 60*, Article 102383.

Coombs, C. (2020). Will COVID-19 be the tipping point for the intelligent automation of work? A review of the debate and implications for research. *International Journal of Information Management, 55*, Article 102182.

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science, 48*(1), 24–42.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982–1003.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. *International Journal of Information Management, 48*, 63–71.

Dwivedi, Y. K., Hughes, D. L., Coombs, C., Constantiou, I., Duan, Y., Edwards, J. S., … Prashant, P. (2020). Impact of COVID-19 pandemic on information management research and practice: Transforming education, work and life. *International Journal of Information Management, 55*, Article 102211.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., … Eirug, A. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 57*, Article 101994.

Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., … Krishen, A. S. (2021). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management, 59*, Article 102168.

Fiske, S. T., Cuddy, A. J., & Glick, P. (2007). Universal dimensions of social cognition: Warmth and competence. *Trends in Cognitive Sciences, 11*(2), 77–83.

Fügener, A., Grahl, J., Gupta, A., & Ketter, W. (2021). Will humans-in-the-loop become borgs? Merits and pitfalls of working with AI. *MIS Quarterly, 45*(3b), 1527–1556.

Gagné, C. L., & Shoben, E. J. (1997). Influence of thematic relations on the comprehension of modifier–noun combinations. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 23*(1), 71.

Gebauer, J., & Shaw, M. J. (2004). Success factors and impacts of mobile business applications: results from a mobile e-procurement study. *International Journal of Electronic Commerce, 8*(3), 19–41.

Gelbrich, K., Hagel, J., & Orsingher, C. (2021). Emotional support from a digital assistant in technology-mediated services: Effects on customer satisfaction and behavioral persistence. *International Journal of Research in Marketing, 38*(1), 176–193.

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, 213–236.

GrandViewResearch. (2020). *A*rtificial Intelligence Market Size, Share and Trends Analysis Report by Solution (Hardware, Software, Services), by Technology (Deep Learning, Machine Learning), by End Use, by Region, and Segment Forecasts

2020–2027. Retrieved January 6, 2021 from ⟨https://www.gr&viewresearch.com/industry-analysis/artificial-intelligence-ai-market⟩.
Granulo, A., Fuchs, C., & Puntoni, S. (2019). Psychological reactions to human versus robotic job replacement. *Nature Human Behaviour, 3*(10), 1062–1069.
Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management, 49*, 157–169.
Hampton, J. A. (1987). Inheritance of attributes in natural concept conjunctions. *Memory & Cognition, 15*(1), 55–71.
Hampton, J. A. (1988). Overextension of conjunctive concepts: Evidence for a unitary model of concept typicality and class inclusion. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 14*(1), 12.
Haslam, N., Kashima, Y., Loughnan, S., Shi, J., & Suitner, C. (2008). Subhuman, inhuman, and superhuman: Contrasting humans with nonhumans in three cultures. *Social Cognition, 26*(2), 248–258.
Hayes, A. F. (2017). Introduction to Mediation, Moderation, and Conditional Process. *Analysis: A Regression-based Approach*. New York, NY: Guilford Publications.
Hertz, N., & Wiese, E. (2019). Good advice is beyond all price, but what if it comes from a machine? *Journal of Experimental Psychology: Applied, 25*(3), 386.
Ho, A., Hancock, J., & Miner, A. S. (2018). Psychological, relational, and emotional effects of self-disclosure after conversations with a chatbot. *Journal of Communication, 68*(4), 712–733.
Hoffman, D. L., & Novak, T. P. (2018). Consumer and object experience in the internet of things: An assemblage theory approach. *Journal of Consumer Research, 44*(6), 1178–1204.
Hu, Q., Lu, Y., Pan, Z., Gong, Y., & Yang, Z. (2021). Can AI artifacts influence human cognition? The effects of artificial autonomy in intelligent personal assistants. *International Journal of Information Management, 56*, Article 102250.
Huang, M.-H., Rust, R., & Maksimovic, V. (2019). The feeling economy: Managing in the next generation of artificial intelligence (AI). *California Management Review, 61*(4), 43–65.
Huang, M.-H., & Rust, R. T. (2021b). A framework for collaborative artificial intelligence in marketing. *Journal of Retailing*. https://doi.org/10.1016/j.jretai.2021.03.001. in press.
Huang, M.-H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research, 21*(2), 155–172.
Huang, M.-H., & Rust, R. T. (2021aaa). Engaged to a robot? The role of AI in service. *Journal of Service Research, 24*(1), 30–41.
Huang, M.-H., & Rust, R. T. (2021bb). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science, 49*(1), 30–50.
Huang, Y., Gursoy, D., Zhang, M., Nunkoo, R., & Shi, S. (2021). Interactivity in online chat: Conversational cues and visual cues in the service recovery process. *International Journal of Information Management, 60*, Article 102360.
Jörling, M., Böhm, R., & Paluch, S. (2019). Service robots: Drivers of perceived responsibility for service outcomes. *Journal of Service Research, 22*(4), 404–420.
Jussupow, E., Spohrer, K., Heinzl, A., & Gawlitza, J. (2021). Augmenting medical diagnosis decisions? An investigation into physicians' decision-making process with artificial intelligence. *Information Systems Research, 32*(3), 713–735.
Kim, S. Y., Schmitt, B. H., & Thalmann, N. M. (2019). Eliza in the uncanny valley: Anthropomorphizing consumer robots increases their perceived warmth but decreases liking. *Marketing Letters, 30*(1), 1–12.
Kim, T. W., & Duhachek, A. (2020). Artificial Intelligence and persuasion: a construal-level account. *Psychological Science, 31*(4), 363–380.
Koschmann, A., & Bowman, D. (2018). Evaluating marketplace synergies of ingredient brand alliances. *International Journal of Research in Marketing, 35*(4), 575–590.
Liao, J., Hansen, P., & Chai, C. (2020). A framework of artificial intelligence augmented design support. *Human–Computer Interaction, 35*(5–6), 511–544.
Lin, T.-C., & Huang, C.-C. (2008). Understanding knowledge management system usage antecedents: An integration of social cognitive theory and task technology fit. *Information & Management, 45*(6), 410–417.
Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. *Journal of Consumer Research, 46*(4), 629–650.
Longoni, C., & Cian, L. (2020). Artificial intelligence in utilitarian vs. hedonic contexts: The "word-of-machine" effect. *Journal of Marketing*, 0022242920957347.
Luo, X., Qin, M. S., Fang, Z., & Qu, Z. (2021). Artificial intelligence coaches for sales agents: Caveats and solutions. *Journal of Marketing, 85*(2), 14–32.
Marr, B. (2019). Artificial Intelligence Can Now Write Amazing Content-What Does That Mean for Humans? Retrieved July 25, 2020 from ⟨https://www.forbes.com/sites/bernardmarr/2019/03/29/artificial-intelligence-can-now-write-amazing-content-what-does-that-mean-for-humans/#37605f8450ab⟩.
McLeay, F., Osburg, V. S., Yoganathan, V., & Patterson, A. (2021). Replaced by a robot: Service implications in the age of the machine. *Journal of Service Research, 24*(1), 104–121.
Mende, M., Scott, M. L., van Doorn, J., Grewal, D., & Shanks, I. (2019). Service robots rising: How humanoid robots influence service experiences and elicit compensatory consumer responses. *Journal of Marketing Research, 56*(4), 535–556.
Meyer-Waarden, L., & Cloarec, J. (2021). "Baby, you can drive my car": Psychological antecedents that drive consumers' adoption of AI-powered autonomous vehicles. *Technovation*, Article 102348.
Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management, 58*(3), Article 103434.
NHTSA. (2017). Automated Driving Systems 2.0: A Vision for Safety. Washington, DC: US Department of Transportation.
Ostrom, A. L., Fotheringham, D., & Bitner, M. J. (2019). Customer acceptance of AI in service encounters: Understanding antecedents and consequences. In *Handbook of Service Science* (Vol. II). New York, NY: Springer.
Parasuraman, A. (2000). Technology Readiness Index (TRI) a multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research, 2*(4), 307–320.
Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined technology readiness index: TRI 2.0. *Journal of Service Research, 18*(1), 59–74.
Park, C. W., Jun, S. Y., & Shocker, A. D. (1996). Composite branding alliances: An investigation of extension and feedback effects. *Journal of Marketing Research, 33*(4), 453–466.
Pillai, R., Sivathanu, B., & Dwivedi, Y. K. (2020). Shopping intention at AI-powered automated retail stores (AIPARS). *Journal of Retailing and Consumer Services, 57*, Article 102207.
Prakash, A. V., & Das, S. (2021). Medical practitioner's adoption of intelligent clinical diagnostic decision support systems: A mixed-methods study. *Information & Management, 58*(7), Article 103524.
Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2021). Consumers and artificial intelligence: An experiential perspective. *Journal of Marketing, 85*(1), 131–151.
Reuters. (2018). Finland Schools Are Testing Out Robot Teachers. Retrieved July 25, 2020 from ⟨https://nypost.com/2018/03/27/finland-schools-are-testing-out-robot-teachers/⟩.
Rust, R. T., & Huang, M.-H. (2021). *The feeling economy: How artificial intelligence is creating the era of empathy*. Springer Nature,.
Sampson, S. E. (2021). A strategic framework for task automation in professional services. *Journal of Service Research, 24*(1), 122–140.
Seeber, I., Bittner, E., Briggs, R. O., De Vreede, T., De Vreede, G.-J., Elkins, A., … Randrup, N. (2020). Machines as teammates: A research agenda on AI in team collaboration. *Information & Management, 57*(2), Article 103174.
Sidaoui, K., Jaakkola, M., & Burton, J. (2020). AI feel you: Customer experience assessment via chatbot interviews. *Journal of Service Management, 31*(4), 745–766.
Smith, E. E., Osherson, D. N., Rips, L. J., & Keane, M. (1988). Combining prototypes: A selective modification model. *Cognitive Science, 12*(4), 485–527.
Song, X., Xu, B., & Zhao, Z. (2022). Can people experience romantic love for artificial intelligence? An empirical study of intelligent assistants. *Information & Management, 59*(2), Article 103595.
Sung, E. C., Bae, S., Han, D.-I. D., & Kwon, O. (2021). Consumer engagement via interactive artificial intelligence and mixed reality. *International Journal of Information Management, 60*, Article 102382.
Swaminathan, V., Gürhan-Canli, Z., Kubat, U., & Hayran, C. (2015). How, when, and why do attribute-complementary versus attribute-similar cobrands affect brand evaluations: A concept combination perspective. *Journal of Consumer Research, 42*(1), 45–58.
Tofangchi, S., Hanelt, A., Marz, D., & Kolbe, L. M. (2021). Handling the efficiency–personalization trade-off in service robotics: A machine-learning approach. *Journal of Management Information Systems, 38*(1), 246–276.
Turja, T., Aaltonen, I., Taipale, S., & Oksanen, A. (2020). Robot acceptance model for care (RAM-care): A principled approach to the intention to use care robots. *Information & Management, 57*(5), Article 103220.
van Doorn, J., Mende, M., Noble, S. M., Hulland, J., Ostrom, A. L., Grewal, D., & Petersen, J. A. (2017). Domo arigato Mr. Roboto: Emergence of automated social presence in organizational frontlines and customers' service experiences. *Journal of Service Research, 20*(1), 43–58.
Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 157–178.
Wang, C., Teo, T. S., & Janssen, M. (2021). Public and private value creation using artificial intelligence: An empirical study of AI voice robot users in Chinese public sector. *International Journal of Information Management, 61*, Article 102401.
Wang, J., & Lewis, M. (2007). Human control for cooperating robot teams. *2007 2nd ACM/IEEE International Conference on Human-Robot Interaction (HRI) (* (pp. 9–16). IEEE.
Waters, R. (2020). Valued at $30bn, Waymo Considers Its Next Move. Retrieved July 25, 2020 from ⟨https://www.ft.com/content/ed8dc4ca-5eaf-11ea-b0ab-339c2307bcd4⟩.
Waytz, A., & Norton, M. I. (2014). Botsourcing and outsourcing: Robot, British, Chinese, and German workers are for thinking—not feeling—jobs. *Emotion, 14*(2), 434.
Wesche, J. S., & Sonderegger, A. (2019). When computers take the lead: The automation of leadership. *Computers in Human Behavior, 101*, 197–209.
Wisniewski, E. J. (1996). Construal and similarity in conceptual combination. *Journal of Memory and Language, 35*(3), 434–453.
Xiao, L., & Kumar, V. (2021). Robotics for customer service: A useful complement or an ultimate substitute? *Journal of Service Research, 24*(1), 9–29.
Zhang, D., Pee, L., & Cui, L. (2021). Artificial intelligence in E-commerce fulfillment: A case study of resource orchestration at Alibaba's Smart Warehouse. *International Journal of Information Management, 57*, Article 102304.
Zhu, D. H., & Chang, Y. P. (2020). Robot with humanoid hands cooks food better? Effect of robotic chef anthropomorphism on food quality prediction. *International Journal of Contemporary Hospitality Management*.