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An investigation on trust in AI-enabled collaboration: Application of AI-Driven chatbot in accommodation-based sharing economy

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ABSTRACT

Several measures taken to control the spread of the COVID-19 pandemic have severely disrupted the accommodation sharing sector. This study attempts to find solutions to aid the recovery of the accommodation sharing sector via team efforts. Accordingly, we focus on the integration of artificial intelligence (AI) and collaboration. Despite the significant developments in AI technologies, there exists no research considering the application of AI in team collaboration. Utilizing the design science research method and collaboration engineering, we developed an AI-driven prototype system, AI-Driven, for collaboration process recommendation. Qualitative results show that the newly developed tool for collaboration process recommendation has achieved satisfactory performance. Furthermore, we investigated the antecedents and outcomes of trust in the AI-driven collaboration context. From a practical perspective, we propose several solutions to the challenges looming over the accommodation sharing sector according to collaboration deliverables. Furthermore, a system prototype was developed to facilitate collaboration process recommendation and provide procedural guidance.

1. Introduction

The COVID-19 pandemic is affecting a wide range of industries, among which the hospitality industry, including the accommodation sharing sector, is one of the most affected (Gosling et al., 2020). Measures taken in many countries worldwide to tackle the spread of the COVID-19 pandemic, such as lockdowns and flight cancellations, have profoundly disrupted the accommodation sharing sector (Gerwe, 2021). The devastation caused by the COVID-19 pandemic has even led to a lack of confidence in the viability of the accommodation sharing business in a post-pandemic world (Rinne, 2020). In this context, a fundamental question that needs to be answered is how the accommodation sharing sector will respond to the challenges posed by the COVID-19 pandemic. In today’s highly competitive environment, collaboration encourages team members to share knowledge, communicate, solve problems, and make decisions (Cheng et al., 2017; Hajro et al., 2017; Hu et al., 2009), which is ubiquitous in many different fields, including education and management (Cheng et al., 2017). As collaboration facilitates deliberate efforts toward declared joint goals (Briggs et al., 2003), an effective approach that has been widely considered is to afford collective wisdom. Thus, we attempt to offer solutions to help the accommodation sharing sector recover from the COVID-19 pandemic via teamwork. An ensuing problem is how to achieve productive and successful collaboration. Many organizations are struggling with effective collaboration (Fu et al., 2020) owing to many challenges. Among them, a main challenge lies in inadequate collaboration processes and improper collaboration interventions that can lead to low levels of trust and poor collaboration performance (Cheng et al., 2017; Kirschner et al., 2015).

To this end, many researchers have attempted to discover ways to improve the efficiency and effectiveness of collaborations. Facilitation is an approach to provide support for team collaboration in which facilitators employ a variety of methods, tools, and interventions to help teams achieve their goals (Kolfschoten et al., 2007), which is expected to offer procedural support to coordinate collaboration activities. Facilitated collaboration requires the skills of a professional facilitator who helps team collaboration realize significant improvements in terms of speed, cost, and quality (de Vreede and Briggs, 2019). However, professional facilitators are scarce and expensive; therefore, most organizations cannot afford their services (de Vreede and Briggs, 2019). In response to this challenge, researchers have developed the thinkLets pattern language rooted in collaboration engineering (CE) to codify the abilities of a facilitator so that team members find it easy to learn and reuse (Niederman et al., 2008). By following thinkLets techniques,
practitioners do not require a high level of expertise in facilitated collaboration. Nevertheless, they still need to make good thinkLet choices and then integrate them into a particular collaboration process (de Vreede et al., 2006), which imposes an additional burden on teammates.

CE-based collaboration processes are structured (Cheng et al., 2017). Artificial intelligence (AI) has a high level of competence in addressing structured tasks (Cheng et al., 2022a; Luo et al., 2019), such as process recommendation and procedural guidance in our context. Based on the text analysis approach, AI shows great potential for analyzing both task and team characteristics according to user inputs and subsequently recommending a collaboration process fitting such characteristics. Therefore, AI can act as a facilitator to provide an adequate collaboration process and procedural support for the entire collaboration process. AI-enabled collaboration can not only provide an efficient support for organizations that currently adopt traditional collaboration techniques (e.g., email and social media), but also provide a scientific collaboration process for organizations that have difficulty assembling thinkLets. Despite the potential benefits of AI technologies for well-organized collaboration, to the best of our knowledge, no study has considered the application of AI in team collaboration. The paucity of studies on integrating AI into team collaboration in the field of CE motivated us to develop a prototype system for collaboration process recommendation.

Additionally, we examine users’ trust perceptions in an AI-driven collaboration context because trust is a crucial determinant for the success of both technology (Loh et al., 2021) and collaboration (Cheng et al., 2017). Trusted team collaboration is necessary for team members to feel confident and satisfied with the deliverables they have collectively agreed upon, dependent on trust in both the system and the collaboration process recommended by it. Trust has been frequently discussed in both human-AI interaction and CE contexts (Cheng et al., 2022a; Cheng et al., 2016; Hu et al., 2021; Shin, 2020). It has an influence on user experience while interacting with AI applications and also affects the collaboration performance. Only when the users’ trust level is high will they follow the collaboration process recommended by the system, and thus get trustworthy solutions in an effective manner. Therefore, it is necessary to understand how users develop trust toward both the system prototype and the recommended collaboration process during the human-AI interaction. We further verify the potential positive consequences of trust in an AI-driven collaboration context. Accordingly, this study aims to address the following three research questions:

**RQ1:** Can we design an AI-enabled prototype system to provide procedural support for collaborating toward a specific task?

**RQ2:** Can a trustworthy team collaboration be established and can the collaboration performance be improved? What factors influence the users’ perceived trust during human-AI interaction?

**RQ3:** What are the possible solutions to the challenges faced by the accommodation sharing sector during the COVID-19 pandemic?

This study attempts to determine service recovery strategies in the accommodation sharing sector during the COVID-19 pandemic via team collaboration. Based on CE and the design science research (DSR) method, we first develop a system prototype named *AI-Driven* for recommending a collaboration process according to the team and task features. Multiple iterations are used to optimize the system to a satisfactory level. Participants obtain and follow a credible collaboration process from *AI-Driven* and collaborate in Discussion. Following the collaborative task completion, we summarize the solutions to the challenges and examine users’ trust in the AI-enabled collaboration context. An overview of our study is illustrated in Fig. 1.

The remainder of this paper is organized as follows. In Section 2, we review relevant literature on CE, human-AI interaction, and trust in
collaboration. Section 3 presents our research methodology. The artifact design and performance evaluation are described in Section 4. In Section 5, the evaluation of the optimized system and an investigation into trust are discussed. Finally, Section 6 summarizes the research findings, implications, and limitations.

2. Literature review

2.1. Accommodation-based sharing economy during COVID-19 pandemic

The accommodation-based sharing economy is suffering a severe and unprecedented disruption because of the COVID-19 pandemic (Chen et al., 2020; DuBois, 2020). The unique strengths that encouraged the accommodation sharing sector to develop significantly have become its weaknesses during the COVID-19 pandemic (Gerwe, 2021). Intimate relationships enabled by the accommodation-based sharing economy initially attracted ordinary citizens and individuals to participate in this emerging business. However, social relationship cohesion and consolidation, which were considered as strengths, have led to a potential health hazard during the COVID-19 pandemic (Gerwe, 2021) because of unpredictable contacts in closed spaces. According to a report, weekly bookings on Airbnb from January to May in 2020 fell by 96% in Beijing, 46% in Seoul, and 29% in Milan (DuBois, 2020). In this situation, it is necessary to understand the major challenges confronting the accommodation sharing sector and accordingly propose potential solutions.

2.2. Collaboration engineering

CE was founded and developed to enable organizations without the support of professional facilitators to realize the benefits of collaboration technology (de Vreede and Briggs, 2019). CE is defined as “an approach for the design and deployment of collaborative technologies and collaborative processes to support mission-critical tasks” (Briggs et al., 2003). It has two important aspects: how to design a repeatable and effective collaboration process supported by technology for high-value tasks and how to transfer these designs to practitioners who lack training on tools or techniques (Briggs et al., 2003; de Vreede et al., 2009). CE-based collaboration processes have been applied in various fields and yielded positive consequences, such as improving collaboration performance and establishing trust (Cheng et al., 2016; de Vreede and Briggs, 2019; Fu et al., 2020).

The design patterns language of CE is thinkLets, which involves labeled, packaged facilitation interventions that produce predictable and repeatable collaboration processes (de Vreede et al., 2006). To date, approximately 70 thinkLets modules have been formally documented by CE researchers (Kolfschoten et al., 2006). Each thinkLet is oriented with a concrete group-dynamics intervention (Kolfschoten et al., 2006). Designers need to select corresponding thinkLets according to the six stages of collaboration patterns: generate, reduce, clarify, organize, evaluate, and build consensus (Briggs et al., 2003; de Vreede et al., 2009). Each collaboration process comprises a specific sequential combination of thinkLets that engender different collaboration patterns between team members (Kolfschoten et al., 2006). The combination of different thinkLets provides an opportunity to flexibly design collaborative processes to support different scenarios. We discuss thinkLets in detail in Section 4.

2.3. Conversational AI and human-AI interaction

AI is defined as a computer program that can perform specific tasks in place of a human (Huang and Rust, 2021). A large number of technology companies have devoted considerable efforts toward the development and utilization of AI. From physical robotics in automobile assembly lines to medical decision support systems, AI is playing an increasingly important role in helping or replacing humans in performing tasks (Gursoy et al., 2019). One of the most promising AI applications, namely, conversational agents (Carter, 2018), are disruptive innovations attracting extensive attention from practitioners and researchers. Considerable research focuses on the representative form of conversational agents known as chatbots and examines user responses to their human-like attributes (Hu et al., 2021; Luo et al., 2019; Schanke et al., 2021; Sheehan et al., 2020). For instance, Schanke et al. (2021) investigated how consumers who want to sell used clothes respond to customer service chatbots. Their results indicated that anthropomorphic chatbot features, such as humor, communication delays, and social presence, affect transaction outcomes. Luo et al. (2019) examined the impact of chatbot identity disclosure on consumer responses and found that the disclosure of chatbot identity engenders reduced purchases. Other studies also explored how the anthropomorphism of AI applications influences users’ adoption or resistance intention (Cheng et al., 2022a; Gursoy et al., 2019). Although the existing literature advances our knowledge of human-AI interaction, there is a lack of research on the deployment of AI in team collaboration and on the analysis of the role of AI in improving collaboration performance.

2.4. Trust in collaboration

Trust is frequently mentioned in mutual relationships (Cheng et al., 2017; Jiang and Lau, 2021; Zhao et al., 2020), such as the relationship between buyers and sellers in e-commerce (Tu et al., 2016), between community members (Cheng et al., 2019b), between demanders and suppliers in ridesharing (Cheng et al., 2019a; Cheng et al., 2020), and between humans and AI agents in human-AI interaction (Hu et al., 2021). It refers to a positive and confident expectation of others’ behaviors (McKnight et al., 2002). Trust is critical to cooperation, particularly for a virtual team (Jarvenpaa et al., 1998; Ridings et al., 2002), and could yield positive consequences, including complexity reduction in an uncertain situation with ambiguous and incomplete information (Luthans, 1992) and vulnerability acceptance (Mayer et al., 1995). Therefore, many researchers believe that trust is the key to a successful collaboration or collaborative performance (Cheng et al., 2017; Cheng et al., 2016; Wilson et al., 2006). Given the importance of trust in collaboration, researchers have further shifted their attention to the cultivation of trust within a team. Several factors have been found to influence trust in teams, such as perceived risk factors, including communication (Jarvenpaa et al., 1998; Peters and Manz, 2007), time zone difference, language and cultural differences (Cheng et al., 2017), and perceived benefits factors, including leadership, task accomplishment (Cheng et al., 2017), and knowledge sharing (Alsharo et al., 2016). Most existing studies have investigated the impact of institutional factors on trust building between team members. However, an important dimension of trust in the team collaboration setting, namely, trust in the collaboration process, is ignored. Consequently, antecedents and outcomes of trust in the collaboration process, particularly in the context of AI-driven collaboration, are underexplored.

3. Research methods

This study employed CE as the design theory (de Vreede and Briggs, 2019) and DSR as the research method (Hevner et al., 2004). In our study, artifact design includes two parts: collaboration process and prototype system design. Based on the principles of CE, we designed a set of collaboration processes customized for different situations. Adopting the DSR methodology, we developed a system prototype for collaboration process recommendation and improved it by conducting a second iteration based on user evaluations.

DSR is essentially a problem-solving process (Hevner et al., 2004). This methodology provides a paradigm to design and evaluate information technology (IT) artifacts intended to address problems and improve performance (Hevner et al., 2004). IT artifacts are extensively specified as constructs, models, tools, processes, and instantiations (Gregor and Hevner, 2013). DSR provides an opportunity for
information system (IS) research to solve problems encountered in the development of IT artifacts. The core principle of DSR is that the designer needs to understand a design problem and its solution before developing and applying an artifact. There are several guidelines to conduct effective DSR, such as problem relevance, design evaluation, research contribution, design rigor, design as a search process, and research communication (Hevner et al., 2004). Unlike behavioral science, which focuses on explaining and predicting phenomena associated with an identified business need through the development and justification of a theory, design science emphasizes on addressing the need through the building and evaluation of artifacts.

Regarding the collaboration process design, Kolfschoten and de Vreede (2009) proposed the following five stages: task diagnosis, activity decomposition, task-thinkLet choice, agenda building, and design validation (see Fig. 2). During the task diagnosis stage, the team must analyze the collaborative task that needs to be executed, including requirements and constraints on the collaboration process. Once the constraints and requirements regarding the collaboration process have been identified, the team needs to decompose the collaborative task to determine the sequence of steps for the collaboration process in the activity decomposition stage. Next, we transition into the task-thinkLet choice stage, wherein the six general patterns: generate, reduce, clarify, organize, evaluate, and build consensus (Briggs et al., 2006), are used to create an optimal thinkLet sequence. In the agenda building stage, additional planning of activities and instructions for each activity are defined. The designed artifact is tested in a real situation in the design validation stage.

4. Artifact design

In this section, we attempt to integrate AI into team collaboration to provide procedural support when teams discuss possible solutions to challenges faced by the accommodation sharing sector. First, we design collaboration processes that fit different scenarios based on the CE approach. Next, an AI-enabled prototype system is designed to automatically recommend the process by analyzing the characteristics of teams and tasks. Subsequently, a laboratory experiment is conducted to evaluate the performance of our developed system. Based on interview data from the first laboratory experiment, we further optimize the system. Then, we conduct another laboratory experiment to evaluate the optimized system. The results indicate the realization of a satisfactory and trusted collaboration process recommendation system. Finally, according to the interview data from the two laboratory experiments, we investigate members’ trust and summarize the solutions to challenges encountered by the accommodation sharing sector in the next section.

4.1. Collaboration process design

The task-thinkLet choice stage is particularly important. Deciding which thinkLets might be suitable for a given situation and integrating
them into a sequence of the collaboration process are critical for the success of team collaboration. Six general patterns of thinklets are briefly described below (Kolfschoten and de Vreede, 2009).

Generate: Move from having fewer to having more concepts in the pool of concepts shared by the team.
Reduce: Move from having many concepts to a focus on fewer concepts that the team deems worthy of further attention.
Clarify: Move from having less to having more shared understanding of concepts and of the words and phrases used to express them.
Organize: Move from less to more understanding of the relationships among concepts the team is considering.
Evaluate: Move from less to more understanding of the relative value of the concepts under consideration.
Build consensus: Move from having fewer to having more team members who are willing to commit to a proposal.

Based on existing literature on CE, we selected 11 commonly used thinkLet modules to organize and design the collaboration processes, as shown in Table 1. Four experts, a professor engaged in CE research for more than ten years, two PhD candidates and an undergraduate student engaged in CE research for approximately one year, designed collaboration processes by considering all collaboration scenarios they had encountered thus far. First, they performed this task separately. Then, they worked together to classify all suggested scenarios. Next, they were asked to design a suitable collaboration process for each scenario and cross-check the results. If there was an inconsistent opinion regarding a designed collaboration process, they discussed it until an agreement was reached. Ultimately, nine collaboration processes for 11 corresponding collaboration scenarios were obtained (see Appendix A). An example of the collaboration process for leaderless group discussion is illustrated in Fig. 3. The sequence number, activity name, time setting, and collaboration pattern for each thinkLet were labeled.

### 4.2. System architecture

#### 4.2.1. Overview

We designed an AI-driven chatbot called AI-Driven to emulate the best-performing human facilitators in terms of understating collaboration features and recommending adaptive collaboration process recommendations. AI-Driven is a program that enables human–computer conversations via text chats (Luo et al., 2019). An overview of AI-Driven’s system architecture is shown in Fig. 4. Referring to Cui et al. (2017), three engines are designed for managing inputs from different users: fact QA, FAQ, and chit-chat engines. A specific input query from a system user is handled by the corresponding engine in the dialog module. The response can be achieved with a deep-learning-based matching between the input text and knowledge base. AI models based on historical conversation records are trained to customize the collaboration process for teams in the dialog module. Meanwhile, expert opinions and historical records of user input are used to upgrade the process-based knowledge base.

#### 4.2.2. Meta engine

The fact QA engine is designed to respond to queries regarding details of each thinkLet. The functions of the 11 thinkLet modules are stored in the knowledge tuple format in our knowledge base <#, attribute>, where # represents the name of a thinkLet and attribute involves steps for implementing it. A deep-structured semantic model is used to achieve a match between the input and thinkLet name. A fact QA example is shown below.

**Q:** How to brainstorm?

**A:** Steps: 1. Determine the question to discuss and time for discussion. 2. Everyone posts their comments.

The FAQ search engine is designed to answer queries regarding process recommendation. Specifically, given a set of QA pairs \( P = \{ q_i, a_i \} \) and a user input \( q \), the most similar \( q_i \) is found and the corresponding \( a_i \) is returned as the response. This is achieved using bidirectional encoder representations from transformers (BERT). Formally, given a collaboration scenario obtained from a user input \( q_{in} \), an adequate collaboration process \( a_{out} \) is returned in response. A FAQ search example is shown below.

**Q:** What process do we use for a quick discussion?

**A:** Solutions for a quick discussion: 1. BrainStorm 2. FastFocus 3. Concentration 4. StrawPoll 5. Crowbar.

The chit-chat engine is designed to respond to greeting queries, such as...
as “hello,” and questions that cannot be answered by the first two engines, such as “What can you do?” This is achieved with an attention-based long short-term memory (LSTM) sequence-to-sequence model. A chit-chat search example is shown below.

**Q**: What can you do?

**A**: You can ask me about each module and I will show you how to do it.

### 4.2.3. Bidirectional encoder representations from transformers (BERT)

The BERT model (Vaswani et al., 2017) was used for natural language processing. A BERT pre-training model can perform better than the traditional Word2vec in distinguishing polysemous meanings across different contexts, thereby transferring rich knowledge learning (Zhang et al., 2021). The core functionalities of BERT are multi-layer transformer encoders that depend on the self-attention mechanism (Zhang et al., 2021; Vaswani et al., 2017). Fig. 5 shows the architecture of a BERT pre-training language model.

**AI-Driven** is a question-and-answer dialog tool. Fig. 6 shows a screenshot of the improved version of **AI-Driven**, illustrating how the **AI-Driven** system prototype supports the team in automatically recommending a collaboration process and providing procedural support after retrieving information from the keyboard (KB). The users input textual descriptions in the text box, and **AI-Driven** outputs a corresponding response.

### 4.3. System evaluation and improvements

#### 4.3.1. System evaluation and results

College students have a high level of knowledge and are more willing to adopt and accept new technologies. To eliminate the impact of substantial differences in technology-awareness and obtain an accurate system performance assessment, we recruited 24 college students, aged between 18 and 24 years, to participate in our experiment. Among them, 37.5% were males and 62.5% were females. To obtain reliable solutions to the challenges looming over the accommodation sharing sector, we recruited college students majoring in IS, marketing, and business, who had prior team collaboration experience and relevant knowledge about accommodation sharing services. However, they did not have any experience with business recovery strategies during the COVID-19 pandemic. Therefore, the selected subjects were suitable because individuals might be unable to accomplish a goal on their own, but team collaboration is expected to aid in achieving it. The 24 participants were randomly divided into eight teams of three members each.

Each team was asked to discuss two questions: (i) What are the challenges faced by the accommodation sharing sector during the COVID-19 pandemic? and (ii) How does the accommodation sharing sector respond to these challenges? Participants were allotted 20 min to individually think of answers to the questions. Thereafter, the team members needed to work together to determine the final answers for each team. All teams were asked to use the **AI-Driven** chatbot to obtain a recommended collaboration process and were required to follow it to collaborate toward achieving their deliverables (i.e., solutions to the challenges faced by the accommodation sharing sector) in Discussion.

**Discussion** can realize most of the thinkLets modules, which have been used in team collaboration in different domains, including hospitality management and education (Cheng et al., 2017; Fu et al., 2020). We confirmed the collaboration process to the participants and instructed them to familiarize themselves with **Discussion** before the formal team collaboration began. The participants needed to be registered on **Discussion** before they could use it. Each team worked together for up to 45 min. After the team collaboration is complete, one member of each team is appointed as a reporter responsible for reporting the collaboration process followed by her/his team, duration for each module, and deliverables.

We interviewed the participants to evaluate the prototype system. The interview protocol consisted of four parts. First, we asked the participants about their previous experiences in collaboration and the use of collaboration tools. Second, we asked about their perceived trust and perceived satisfaction with both **AI-Driven** and the recommended collaboration process. Additionally, the interviewees were asked about which factors affected their perceived trust and subsequent behavior. Third, we inquired about the benefits of following the recommended collaboration process and whether collaborative performances improved as a result. Finally, we asked open-ended questions regarding
indicated that 80% of the participants had negative attitudes toward and effective by following the recommended process. The results also suggested that team collaboration was more efficient.

Second, the marked phrases and sentences were dichotomized based on their valence, that is, positive and negative perceptions. Third, we summarized the statements related to users’ attitude, collaboration performance, and improvement suggestions from categorized documents. Two authors analyzed the interview data and cross-checked the results. The entire coding process lasted for approximately 15 min. All interviews were recorded using a digital recording device and transcribed for data analysis. We labeled the interview documents as “E1SX” indicating the X-th interviewee in the first experiment. We coded our interview data as follows. First, we marked all phrases and sentences associated with users’ perceptions. Second, the marked phrases and sentences were dichotomized based on their valence, that is, positive and negative perceptions. Third, we summarized the statements related to users’ attitude, collaboration performance, and improvement suggestions from categorized documents. Two authors analyzed the interview data and cross-checked the results. The results suggested that team collaboration was more efficient and effective by following the recommended process. The results also indicated that 80% of the participants had negative attitudes toward Al-Driven, revealing some shortcomings in our prototype system. Specifically, Al-Driven needs further improvements to recommend an accurate process and provide a personalized service. The current system is rigid and recommends the same collaboration process for different scenarios. Moreover, Al-Driven can only identify accurate descriptions related to the collaboration. If the input requirements are vague, the system is not competent enough to handle such cases. In addition, users must repeat their inputs to obtain the instruction for each thinkLet. The interviewees mentioned the following:

“I hope it (system) would be more flexible; then, its recognition would be more accurate. Currently, it is very rigid.” (E1S4).

“The disadvantage may be that repeated input is more troublesome. If it can improve the interaction between people and AI, maybe it would be better. Perhaps, optional recommendation is helpful.” (E1S6).

“The disadvantage is that his recognition requires your input to be very precise. It does not have that kind of fuzzy recognition.” (E1S10).

4.3.2. Second-round iteration

According to the suggestions proposed by interviewees, we improved our system in several ways. First, we added a list of buttons for thinkLets so that users can more easily learn the instructions for each module by clicking a button instead of typing. As shown in Fig. 6, the top of the interface has several clickable buttons to facilitate the understanding of the purpose and operation of each thinkLet. Second, to improve the accuracy of our recommendation algorithm, we expanded the training set to 1,170 conversations regarding team collaboration and retrained our matching model.

4.3.3. Optimized system evaluation

We conducted another laboratory experiment to evaluate the optimized system. The optimized Al-Driven chatbot was used by 21 participants from the previous experiment, among which seven were males and fourteen were females. They were randomly divided into seven teams of three members each. The next set of processes was consistent with those described in Section 4.2.4. Each team in this experiment was asked to discuss the same two questions by following the recommended process using the optimized Al-Driven chatbot. Thereafter, each team was also asked to provide answers to those two questions. Meanwhile, they were asked to document the collaboration processes used, the duration for each thinkLet, and the final response to both questions. We randomly selected four males and eight females from the 21 participants for the interviews. We followed the previous interview protocol and coding procedures described in Section 4.3.1. We coded the interview documents as “E2SY” to indicate the Y-th interviewee in the second experiment. The results indicated that all interviewees reported that the improved version of Al-Driven was satisfactory. They perceived the new system as more convenient and intelligent. Moreover, several interviewees expressed more trust in the optimized system. Participants in the second experiment mentioned the following:

“The level of trust is increased because the shortcomings from users’ feedback have been addressed. Moreover, the interface design is much more user-friendly than before, especially by adding the instruction for each (thinkLet) module.” (E2S5).

“I trust it more, mainly because it recognizes my needs more accurately.” (E2S6).

5. Results

5.1. Trust in Al-enabled collaboration

To obtain antecedents and outcomes of trust in the Al-enabled collaboration context, we coded the interview documents from the two experiments in more detail. Two of the authors analyzed the interview data and cross-checked the results. The entire coding process
went through three rounds, as shown in Fig. 7. First, the key sentences or phrases related to our research questions were identified and labeled. Second, the sentences or phrases with the same meaning were classified into one category, and the categorized documents were marked using a list of keywords. Third, by reviewing the existing literature and theories, we extracted key constructs to describe the categorized documents. The findings are summarized in Fig. 7.

5.1.1. Antecedents of system trust
Four key factors were recognized as the antecedents of trust in AI-Driven: ease of system use, friendliness, intelligence, and privacy invasion. Perceived ease of use of system refers to “the degree to which a person believes that using a particular system would be free of effort” (Davis, 1989). If potential users perceive that the system is difficult to use, or that the effort for using the system far outweighs the possible benefits, they are more likely to not use it. The interviewees mentioned the following:

“The system is very easy to use.” (E1S7).

“The system is more convenient to use.” (E2S11).

Perceived friendliness refers to users’ perception that the AI-enabled system is friendly and willing to help the user. Human-AI interaction is inherently a social interaction (Adam et al., 2021). Humans tend to react to AI-driven agents that exhibit human characteristics in a manner similar to how they react to humans. Therefore, the friendly service provided by AI-Driven generates positive emotions and a high level of trust for users. Some participants claimed the following:

“The user interface is more clear, concise, and intuitive. You can directly find the details of each step of the process at the top of the system interface. These introductions make it feel friendly.” (E2S11).

“I think the system is quite good. Especially for first-time users, it is quite friendly.” (E2S4).

Perceived intelligence refers to the ability of the AI-driven system to “identify and understand users’ input and provide effective output” (Murray et al., 2019; Pillai and Sivathanu, 2020). Users expect AI-Driven to be intelligent. If they feel the system has understood their needs and responded appropriately, they tend to believe the system. The interviewees commented as follows:

“I don’t really understand what it (the system) is saying, and thus perceived trust decreases.” (E1S3).

“It is not very intelligent. Hence, some decisions made by it are less rational.” (E1S9).

“I trust it more because it can identify my needs accurately.” (E2S1).

Perceived privacy invasion refers to a feeling that the system may compromise personal privacy (Ayyagari et al., 2011). Both personal information collection and disclosure result in a high level of perceived privacy invasion (Cheng et al., 2022b). Invasion of privacy leads to the reduction in perceived trust in the system. The interviewees suggested the following:

“I can trust this system. It wasn’t involved in private information collection.” (E1S4).

“There’s no complicated black box for collecting personal information. It’s almost impossible to fool you.” (E1S9).

5.1.2. Antecedents of process trust
We identified three factors as antecedents of trust in the recommended processes: perceived helpfulness, ease of use of process, and task-process fit. Perceived helpfulness is defined as the degree to which team members believe that following the recommended collaboration process would improve their collaborative performance (Davis, 1989). When team members perceive the recommended process to be helpful, they have a high tendency to trust and follow it. Many participants mentioned the following:

“Following the recommended process, I feel the efficiency and outcome of collaboration are good. I have a high level of trust.” (E1S5).

“It’s a very credible and efficient process.” (E1S7).

Perceived ease of use of process is defined here as the degree to which team members believe that following the recommended collaboration process would be free of effort (Davis, 1989). A good process makes collaboration easier and can be achieved in a short time. An easy-to-follow process has the potential to increase the team members’ trust. Our interviewees indicated the following:

“The process is quite easy to implement.” (E1S5).

“The recommended process is standardized and easy to use.” (E1S6).

According to the task-technology fit theory, a perfect match between
technology and task is a prerequisite for technology to play a positive role in individual performance (Goodhue and Thompson, 1995). Similarly, a designed process must have a good fit with the collaborative task that it supports so that it has an expected positive influence on team collaboration. If team members feel that the process can help them accomplish their collaborative task, they tend to trust and follow it. The interviewees expressed the following:

“Our main task was to come up with solutions. So the process felt right—a sequence including brainstorming, sorting, voting on the most appropriate approach.” (E2S4).

“Since the objective of the experiment is to give solutions. We brainstorm first and then sort a series of ideas. The process given by the system is appropriate.” (E2S8).

5.1.3. Trust transfer

The trust transfer theory proposes that an individual can transfer his/her trust from a known entity to an unknown one (Stewart, 2003). For instance, trust toward social commerce members has been proven to be transferred to trust toward a social commerce system (Cheng et al., 2019a; 2019b). In the field of CE, we find that trust in the recommended process can be transferred to trust in the system. This can be mainly attributed to users who have an intuitive sense of whether the process is useful, which determines their perception of the level of intelligence of our developed AI-driven system. The interviewees expressed the following:

“Sometimes, the process recommended to me is different from what I expected. So, I can't say I trust the system very much.” (E1S4).

“I have some faith in the system, because I think the process it recommends is easy to understand.” (E2S10).

5.1.4. Relationship between trust and its outcomes

Our study also pays attention to the relationship between trust and its potential outcomes. The qualitative results show a positive relationship between trust in the recommended process and collaboration performance. When team members hold a high level of trust toward the recommended process, they tend to follow the given guidelines and collaborate effectively with others. Consequently, an improved collaboration performance can be realized. For example, our interviewees argued the following:

“It (process) is very credible and effective. Using the recommended process would enhance the efficiency of decision-making.” (E1S7).

“I feel the process recommended by the optimized system has been simplified, and thus our discussion is more efficient.” (E2S12).

In addition, there is a positive relationship between trust in AI-Driven and the intention to use it in the future. If team members believe in the system for a recommendation of an efficient process, they are more likely to employ it to obtain a collaboration process when they need to work together to solve problems. Our interviewees expressed the following:

“I will also consider using this system for future team work. In the process of using this system, I think the team members have a good experience of using this system.” (E2S1).

“If we need to have a more formal team discussion, we’ll probably use it (system). It can provide a helpful process.” (E2S6).

To better understand the extent to which each factor contributes to the development of trust and relationships among constructs proposed in this study, we adopted a team members’ trust onion model (TOM) to summarize our findings (Cheng et al., 2020), as shown in Fig. 8. The color used in the TOM symbolizes the frequency with which the factor is mentioned (Cheng and Macaulay, 2014). The factors mentioned by more
than 50% of the participants are indicated by red circles; those mentioned by 20%–50% of the participants are shown in yellow circles; and those mentioned by less than 20% of the participants are indicated in green circles (Cheng and Macaulay, 2014). The mentioned trust factors and frequency are summarized in Table 2. It was found that perceived ease of use of the system was the prominent factor influencing trust in AI-Driven, followed by perceived friendliness, perceived intelligence, and perceived privacy invasion. This suggested that teams who have to complete collaborative tasks often want to have an easy-to-use system to provide timely procedural support. Additionally, we found that perceived ease of use and perceived helpfulness were the two most important factors determining the members’ trust in the recommended process, followed by perceived task-process fit. This implies that team members are more concerned about how well the process solves their task. In addition, a high level of trust in the process increases the collaboration performance, whereas a high level of trust in the system increases its usage intention.

5.2. Solutions to challenges in accommodation sharing sectors

Accommodation-based sharing economy encourages interaction with strangers, thereby increasing the risk of COVID-19 infection. According to the team collaboration deliverables, challenges are identified and solutions are proposed at different levels. At the country level, measures such as lockdowns and flight cancellations discourage consumers from making travel plans, which essentially leads to a decline in revenue for the entire hotel industry. With the dramatic development of digital technology, the accommodation sharing sector is being encouraged to adopt metaverse and virtual reality technologies to create virtual social, shopping, and house selection scenes, thereby attracting more potential tourists to the virtual tourism world. At the individual level, the lack of cleanliness, sharing space, or touching an object that may have come in contact with a COVID-19 infected individual increases the perceived risk of COVID-19 infection. Therefore, the accommodation sharing sector must do everything possible to allay public concerns regarding COVID-19 infection. Several solutions are proposed, including well-developed and strict cleanliness and safety protocols, cleanliness information transparency, and restrictions on travelers from high-risk areas.

6. Conclusion

6.1. Summary of results

Given the devastating impact of the COVID-19 pandemic on the accommodation sharing sector, this study identifies the related challenges and proposes substantial solutions. We rely on team collaboration to find potential solutions to such challenges. To this end, this study, based on the DSR and CE approach, developed a system prototype named AI-Driven to automatically provide a suitable collaboration process for a specific scenario. Based on qualitative data, the developed system offers answers to the three research questions mentioned in Section 1.

First, we consider RQ1: Can we design an AI-enabled prototype system to provide procedural support for collaborating toward a specific task? After two rounds of iteration, we address the gap between users’ expectation and system performance and demonstrate the validity of the processes recommended by AI-Driven for improving collaboration outcomes. AI-Driven can provide procedural support by recommending an adequate collaboration process and giving guidelines for each collaboration step; consequently, an effective and efficient collaboration is achieved.

Second, we consider RQ2: Can a trustworthy team collaboration be established and can the collaboration performance be improved? What factors influence the users’ perceived trust during human-AI interaction? Our qualitative results indicate that a trusted team collaboration environment has been developed. Teams reach an effective and efficient collaboration by following the recommended collaboration. We also discuss antecedents and outcomes of users’ perceived trust. Four factors: perceived ease of use of system, perceived friendliness, perceived intelligence, and perceived privacy invasion, influence team members’ perceived trust in AI-Driven. In addition, three factors influencing the team members’ perceived trust in the processes recommended by AI-Driven are recognized: perceived helpfulness, perceived ease of use of process, and perceived task-process fit. Regarding the positive consequences of trust, we find that system trust has a positive impact on the team members’ intention to use AI-Driven. The team members who have a high level of trust in AI-Driven are more likely to use it to obtain a viable collaboration process. In addition, trust in the recommended process has a positive impact on collaboration performance. The more team members trust the recommended process by AI-Driven, the more they are willing to follow the process to collaborate; this results in a coordinated and effective collaboration.

Third, we consider RQ3: What are the possible solutions to the challenges faced by the accommodation sharing sector during the COVID-19 pandemic? The collaborative task in our study is to discuss the challenges faced by the sharing accommodation sector and propose solutions. The results of the discussion indicate that a challenge faced by the accommodation sharing sector is policy constraints at the country level. Another one is the consumers’ concern regarding COVID-19 infection at the individual level. Subsequently, several solutions to such challenges at different levels are proposed. Service providers can utilize digital technologies to create a virtual tourism experience for consumers. Meanwhile, it is critical to provide a safety and virus-free accommodation environment via strict sterilization and disinfection measures.

6.2. Theoretical implications

One contribution of our study is to provide a new train of thought for solving several management problems in practice, such as service recovery in the accommodation sharing sector during the COVID-19 pandemic. Most relevant research on the challenges and implications for shared-based accommodation businesses are based on case studies and systematic literature reviews (Gossling et al., 2020; Gerwe, 2021). Relying on CE, our study provides a new perspective to address practical problems effectively, that is, using team collaborations that follow a well-organized process.

Another contribution is the convergence of AI and facilitated collaboration driven by practical problems. Many studies have paid attention to the application of AI in various domains, including e-commerce (Cheng et al., 2022a; Ngai et al., 2021), hospitality (Prentice et al., 2020), and e-health (Abd-Alrazaq et al., 2019). There are also many studies on improving collaboration performance by optimizing the designed processes (Cheng et al., 2017; Fu et al., 2020). To the best of our knowledge, there is a lack of research on whether AI plays an important role in team collaboration performance. Employing the DSR methodology, we designed and evaluated an AI-driven system that can be used to recommend a collaboration process for user-typed collaborative scenarios. Therefore, we believe this study provides a prospective insight for future studies on AI and CE. Future research on how AI affects team collaboration performance as a teammate should be conducted.

### Table 2

Summary of antecedents of trust (N = 27).  

| Trust          | Antecedents of trust (abbreviation) | Frequency |
|----------------|------------------------------------|-----------|
| Trust in system| Perceived ease of use of system (PEUS) | 74.07%    |
|                | Perceived friendliness (PF)        | 29.62%    |
|                | Perceived intelligence (PIN)       | 51.85%    |
|                | Privacy invasion (PI)              | 7.4%      |
| Trust in process| Perceived ease of use of process (PEUP) | 62.96%    |
|                | Perceived helpfulness (PH)         | 55.55%    |
|                | Perceived task-process fit (PTPF)  | 33.33%    |
For instance, future research could explore perceived satisfaction with the collaboration process and outcome when AI acts as a teammate in collaboration with other members.

Our findings also contribute to the existing knowledge on trust. Existing literature mostly regards trust in the collaboration setting as a general concept (Cheng et al., 2017). However, this study investigates trust in two refined dimensions: trust in the system and trust in the collaboration process. Moreover, trust transfer has been proven to exist in the AI-driven collaboration context, and thus, our work successfully extends the trust transfer theory to a new field of study. Additionally, our study uncovers the antecedents of two dimensions of trust. The paucity of relevant research on the integration of AI and CE offers opportunities for us to discover several interesting and domain-specific factors that influence a team member’s trust in the system and process. Finally, positive outcomes of trust in the AI-driven collaboration context are also found and verified.

6.3. Practical implications

Our study has several practical implications. First, the collaborative task in our study was to discuss the challenges faced by the accommodation-sharing sector to improve service quality and counter the risks posed by the COVID-19 pandemic. Second, drawing upon the CE design, this study develops a system prototype named AI-Driven, which can recommend a collaboration process for a specific collaboration scenario. According to our evaluations, both the system and the recommended processes are trustworthy. Following the process recommended by AI-Driven, team members could achieve a productive collaboration. Second, our study addresses a collaboration issue in management practice and provides insights for organizations to rely on advanced IT to avoid uncoordinated and inefficient collaborations. Both AI-Driven and Discussion provide technical options for team collaboration. Additionally, managers could further extend the process design solutions to better implement interventions for team collaboration.

6.4. Limitations and future research

Our study has several limitations and therefore provides scope for future research. First, our sample population is limited to college students, leading to a concern regarding the generalization of our findings. Future studies should recruit a more diverse sample population, including corporate employees, to participate in natural field experiments to validate our results. Second, while we asked subjects to recall past collaboration experiences and compare the collaboration efficiency in the absence or presence of AI, this study cannot really examine whether collaboration in the absence of AI is less efficient and uncoordinated owing to memory bias. Even without the help of AI, it is possible for teammates to collaborate well as long as the collaborative task is perceived to be easy. Therefore, it would behoove researchers to conduct an A/B testing experiment to investigate the collaboration performance with and without AI guidance. Third, although our study identifies the key antecedents and positive consequences of trust, we did not test these effects statistically. Hence, it is necessary to validate our arguments through a quantitative study with a larger and more diverse sample.

CRediT authorship contribution statement

Xusen Cheng: Project administration, Conceptualization, Data curation, Formal analysis, Funding acquisition, Writing – original draft, Writing – review & editing. Xiaoping Zhang: Methodology, Formal analysis, Writing – original draft. Bo Yang: Methodology, Formal analysis, Writing – review & editing. Yaxin Fu: Software, Validation.

Declaration of Competing Interest

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

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Appendix A. Designed collaboration process for different scenarios

| No. | Scenarios and collaboration processes |
|-----|--------------------------------------|
| 1   | Leaderless group discussion:         |
|     | BrainStorm—>FastFocus—>ThemeSeeker—>PopcornSort—>BuckerWalk |
| 2   | Leader participatory group:          |
|     | BrainStorm—>FastFocus—>ThemeSeeker—>PopcornSort—>BuckerWalk |
|     | —>StrawPoll—>CrowBar—>MoodRing      |
| 3   | Discussion about inconsistent opinions: |
|     | BrainStorm—>PointCountPoint          |
| 4   | Obtain more than one topic for discussion: |
|     | LeafHopper—>BuckerWalk—>CrowBar     |
| 5   | Group members have different levels of expertise in the different topics: |
|     | LeafHopper—>BuckerWalk—>CrowBar     |
| 6   | Small group (less than five members): |
|     | BrainStorm—>FastFocus—>ThemeSeeker—>PopcornSort—>BuckerWalk |
| 7   | Rank and vote on decisions:          |
|     | BrainStorm—>FastFocus—>PopcornSort—>BuckerWalk |
|     | —>StrawPoll—>CrowBar                |
| 8   | Evaluate a decision and reach an agreement: |
|     | BrainStorm—>FastFocus—>StrawPoll—>CrowBar |
| 9   | Fast discussion (Limited time):      |
|     | BrainStorm—>FastFocus—>Concentration—>StrawPoll—>CrowBar |
| 10  | Come up with a series of plans and strategies: |
|     | BrainStorm—>FastFocus—>ThemeSeeker—>PopcornSort—>BuckerWalk |

(continued on next page)
References

Abdi-alrazaq, A.A., Alajlani, M., Alawwan, A.A., Bewick, R.M., Gardner, P., Househ, M., 2019. An overview of the features of chatbots in mental health: A scoping review. Int. J. Med. Inform. 132, 103078.

Adam, M., Wessel, M., Beelisse, A., 2021. AI-based chatbots in customer service and their effects on user compliance. Electron. Mark. 31 (2), 427–445.

Alsharo, M., Gregg, D., Ramirez, R., 2016. Virtual team effectiveness: The role of knowledge sharing and trust. Inf. Manage. 54 (4), 479–490.

Ayagari, R., Grover, V., Purvis, R., 2011. Technostrats: Technological antecedents and implications. MIS. Q. 35 (4), 831–858.

Briggs, R.O., de Vreede, G.J., Nunamaker, J.F., 2003. Collaboration engineering with thinklets to pursue sustained success with group support systems. J. Manage. Inf. Syst. 19 (4), 31–64.

Cheng, X., Xu, L., Lu, Y., 2020. An investigation into sharing economy enabled ridesharing drivers’ trust: A qualitative study. Electro. Commer. Res. Appl. 40, 100556.

Cheng, X., Su, L., Luo, X., Benitez, J., Cai, S., 2022b. The good, the bad, and the ugly: Impact of analytics and artificial intelligence-enabled personal information collection on privacy and participation in ridesharing. Eurp. J. Inf. Syst. 31 (3), 339–363.

Cui, L., Huang, S., Wei, F., Tan, C., Duan, C., Zhou, M., 2017. Superagent: A customer service chatbot for e-commerce websites. Proceedings of Association for Computational Linguistics 97–102.

Davis, F.D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS. Q. 13 (3), 319–340.

de Vreede, G.J., Briggs, R.O., 2019. A program of collaboration engineering research and practice: Contributions, insights, and future directions. J. Manage. Inf. Syst. 36 (1), 74–119.

de Vreede, G.J., Briggs, R.O., Massey, A.P., 2009. Collaboration engineering: Foundations and opportunities: Editorial to the special issue on the Journal of the Association of Information Systems. J. Assoc. Inf. Syst. 10 (3), 121–137.

de Vreede, G.J., Kolfschoten, G.L., Briggs, R.O., 2006. ThinkLet: A collaboration engineering pattern language. Int. J. Comput. Appl. Technol. 25 (2–3), 140–154.

Dulbois, D., 2020. Impact of the coronavirus on global short-term rental markets. https://www.airdna.co/blog/coronavirus-impact-on-global-short-term-rental-markets.

Fu, S., Cheng, X., Su, L., Bilghian, A., Okumus, F., 2020. Designing collaboration process facilitation in hotel management teams to improve collaboration performance. Int. J. Hospitality Manage. 88, 102527.

Gerwe, 2021. The Covid-19 pandemic and the accommodation sharing sector: Effects and prospects for recovery. Technol. Forecast. Soc. Change. 187, 120733.

Goodhue, D.L., Thompson, R.L., 1995. Task-technology fit and individual performance. MIS. Q. 19 (2), 213–233.

Güssling, S., Scott, D., Hall, C.M., 2020. Pandemics, tourism and global change: A rapid assessment of COVID-19. J. Sustainable Tourism 29 (1), 1–20.

Gregor, S., Hevner, A.R., 2013. Positioning and presenting design research for maximum impact. MIS. Q. 37 (2), 337–355.

Gursoy, D., Chi, O.H., Lu, L., Nunkoo, R., 2019. Consumers acceptance of artificially intelligent (AI) use in service delivery. Int. J. Inf. Manage. 49, 157–169.

Hajro, A., Gibson, C.B., Pudelko, M., 2017. Knowledge exchange processes in multicultural groups: Linking organizational diversity climates to groups’ effectiveness. Acad. Manage. J. 60 (1), 345–372.

Hevner, A.R., March, S.T., Park, J., Ram, S., 2004. Design science in information systems research. MIS. Q. 28 (1), 75–105.

Huang, M.H., Rust, R., 2021. Engaged to a robot? The role of AI in service. J. Serv. Res. 24 (1), 30–42.

Jarvenpa, S.L., Knoll, K., Leidner, D.E., 1998. Is anybody out there? Antecedents of trust in global. J. Manage. Inf. Syst. 14 (4), 29–64.

Jiang, Y., Luo, A.K.W., 2021. Roles of consumer trust and risks on continuance intention in the sharing economy: An empirical investigation. Electro. Commer. Res. Appl. 47, 110102.

Kirschen, P.A., Kreijiks, K., Phelici, C., Fransen, J., 2015. Awareness of cognitive and social behaviour in a CSCL environment. J. Comput. Assist. Learn. 31 (1), 59–77.

Kolfschoten, G.L., Briggs, R.O., de Vreede, G.J., Jacobs, P.H.M., Appelman, J.H., 2006. A conceptual foundation of the thinklets concept for collaboration engineering. Int. J. Hum. Comput. Stud. 64 (7), 611–621.

Kolfschoten, G.L., de Vreede, G.J., 2009. A design approach for collaboration processes: A multimethod design science study in collaboration engineering. J. Manage. Inf. Syst. 26 (1), 225–256.

Kolfschoten, G.L., Hengst-Bruggeling, M.D., de Vreede, G.J., 2007. Issues in the design of facilitated collaboration processes. Group. Decis. Negot. 16 (4), 347–361.

Loh, X.M., Lee, Y.H., Tan, G.H., Ooi, K.B., Dwivedi, Y.K., 2021. Switching from cash to mobile payment: What’s the hold-up? Internet. Res. 31 (1), 376–399.

Lu, B.Z., Fan, W.G., Zhou, M., 2016. Social presence, trust, and social commerce purchase intention: An empirical research. Comput. Hum. Behav. 56, 225–237.

Luo, X., Yang, Z., Fu, S., 2019. Frontiers: machines vs humans: the impact of artificial intelligence chatbot disclosure on customer purchases. Market. Sci. 38 (6), 937–947.

Latham, K., 1992. Organizational behavior. McGraw-Hill, New York.

Mayer, R.C., Davis, J.H., Schoorman, F.D., 1995. An integrative model of organizational trust. Acad. Manage. Rev. 20 (3), 709–734.

Mcknight, D.H., Choudhury, V., Kacmar, C., 2002. Developing and validating trust measures for e-commerce: An integrative typology. Inf. Syst. Res. 13 (3), 344–359.

Murray, J., Elms, J., Curran, M., 2019. Examining empathy and responsiveness in a high-context service chatbots. Inf. Syst. Res. 32 (3), 736–751.

Ngai, E.W.T., Lee, M.C.M., Luo, M., Chan, P.S.L., Liang, T., 2021. An intelligent knowledge-based chatbot for customer service. Electro. Commer. Res. Appl. 50, 101098.

Niederman, F., Briggs, R., de Vreede, G.J., Kolfschoten, G., 2008. Extending the contextual and organizational elements of adaptive structuration theory in GIS research. J. Assoc. Inf. Syst. 9 (10), 633–652.

Peters, L.M., Manz, C.C., 2007. Identifying antecedents of virtual team collaboration. Team. Perform. Manage. 13 (3), 117–129.

Pillar, R., Sivathanu, B., 2020. Adoption of AI-based chatbots for hospitality and tourism. Int. J. Cont. Hospitality. Manage. 32 (10), 3199–3226.

Prenice, C., Weaven, S., Wong, L.A., 2020. Linking AI quality performance and customer engagement: The moderating effect of AI preference. Int. J. Hospitality. Manage. 90 (8), 10329.

Ridings, C.M., Gefen, D., Arizna, B., 2002. Some antecedents and effects of trust in virtual communities. J. Strategic. Inf. Syst. 11 (3–4), 271–295.

Rinne, A., 2020. Coronavirus: The end of the sharing economy, or a new beginning? https://medium.com/swlh/coronavirus-the-end-of-the-sharing-economy-or-a-new-beginning-8142acbb7130.

Schanke, S., Burtch, G., Ray, G., 2021. Estimating the impact of ‘humanizing’ customer service chatbots. Inf. Syst. Res. 32 (3), 736–751.

Sheehan, B., Jin, H.S., Gottlieb, U., 2020. Customer service chatbots: Anthropomorphism and perception. J. Bus. Res. 115, 141–157.

Shin, D., 2021. The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. Int. J. Hum. Comput. Stud. 146, 102551.

Stewert, K.J., 2003. Trust transfer on the world wide web. Organ. Sci. 14 (1), 5–17.

Vawani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A., Kaiser, L., Polosukhin, L., 2017. Attention is all you need. Proceedings of the 31st International Conference on Neural Information Processing Systems. New York, 6000-6010.

Willems, L.M., Straus, S.G., Mcevoy, B., 2004. All in due time: The development of trust in computer-mediated and face-to-face teams. Organ. Behav. Hum. Dec. 99 (1), 16–33.

X. Cheng et al.