Article

How does an Intelligence Chatbot Affect Customers Compared with Self-Service Technology for Sustainable Services?

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Abstract: To gain competitive advantages and sustainable service innovation, hotels are considering artificial intelligence technologies (AI), including robots, kiosks for service automation and chatbots. However, due to the change of the service process and unfamiliar communication interface, hotel customers may have difficulties in adopting the new change. In this paper, we tried to find out if the failure of AI-based services would affect customers’ perception. For this, we designed the experiment by separating AI (i.e., chatbot) services and self-service technology (SST, i.e., pad) services and service failures and successful cases, respectively. As a result, SST showed more positive perceptions and revisit intention in the successful service situation. The service failure situation showed no differences between chatbot and SST. In addition, novelty and the need for interaction characteristics of customers showed significant differences between groups in terms of service success and failure, respectively. Additionally, we explored negative word-of-mouth (WOM) to learn further effects by service failures and successes.

Keywords: chatbot; self-service technology; service failure; hotel; status quo bias theory; artificial intelligence

1. Introduction

Artificial intelligence (AI) is an artefact based on computer science and machine-learning studies to extend human intelligence. Early-era AI research developers and researchers focused on how to program human’s experiences to solve problems. More recently, empirical knowledge collected from big data is used to develop a series of algorithms to deal with more complex and service-oriented problems on their own [1]. These processes are becoming used more and more in the real-world business environment, as the amount of data that can be learned increases and the technology that can handle it is underpinned [2]. Recently, many industries, such as financial, logics, and education, are actively using AI for services.

In the era of untact, businesses come to face difficult questions on how to change the way of communicating with customers. To conducting sustainable businesses, utilizing new technologies for solving this issue is one of the urgent requirements for the tourism industry. Chatbot, a leading technology applied with AI, is developing and operating services in various industries and businesses. The chatbot market revenue worldwide is expected to grow more than 10 times by 2027 [3], with users recognizing it as a means to communicate smoothly with companies [4]. In line with the stream, several innovative companies in the hospitality industry have begun to use AI technology. For example, hotels (e.g., Aloft hotel) are using robot services while online travel agencies (e.g., Expedia) are using chatbot services there are services, such as service robot utilization in hotels and a chatbot service in...
online travel agencies. It should be noted that conversational chatbots can help in collecting much larger sets of textual data in terms of scale and variety than any other means at a personalized contact level. Therefore, not only the use of chatbots can be a promising approach for cost reduction, but also it is directly related to a more sustainable society for people who are in need [5].

Previous AI and hospitality studies have discussed the application of AI in the hospitality industry, and the future of AI and hospitality industries [6]. Researchers have also investigated the effectiveness of AI utilization through research on the pros and cons of introduction and the design and construction of a chatbot [7]. In addition, there are empirical studies on the improvement of hotel organization performance that the introduction of a chatbot can bring [8].

On the other hand, due to the nature of the hospitality industry, failure of the service could be caused by failure to properly respond to the number of different cases that could be generated in service encounters. This may affect a customer’s trust and loyalty in the entity, resulting in financial and non-financial losses to the firm. Still, research has yet to be done on service failures and recovery from the utilization of AI in the hospitality industry.

Therefore, we set the research question about how the failure of AI service in hotel affect the customers’ perception and behavior intention. To derive a discussion and implication of our research question, we established the next three research goals. First, to investigate customers’ awareness and intention according service situation (service success/failure) and service type (chatbot/SST). Second, to explore how customers’ inherent traits can be involved in their perceptions. Third, to scrutinize the relative importance of a customers’ awareness or behavior intention caused by a service failure.

To empirical approach about our research goals, we applied the Status Quo Bias Theory to explain the successful service situation. We also worked to reveal how service failure in two service interfaces (chatbot, pad) would affect customers’ attitudes and the degree of negative behavior. We wanted to see how the user’s characteristics could make a difference in the success or failure of services through a chatbot and SST. To this end, we applied the novelty characteristics of individuals with the situation of successful service. The characteristics of the need for interaction was adopted for the service-failure situation. Moreover, additional analysis was conducted on the difference between success and failure by applying variables that could result from the failure of the technology.

Through this research, we discuss the success and failure of progressive forms of services to be applied to the hotel industry, and proper reaction for service recovery. Thus, it can work as a basic reference for a company when preparing service innovation. Moreover, it could be a basic step toward a study of AI and service failure.

2. Background

2.1. AI and Hospitality

Artificial intelligence is defined as “systems that combine sophisticated hardware and software with elaborate databases and knowledge-based processing models to demonstrate characteristics of effective human decision making.” ([9], p. 28). AI has grown rapidly in recent years because of advancements in computer science and technology. A McKinsey report ranks the use of AI by companies represented in 13 industrial areas [4]. According to the report, travel and tourism were at the lowest level among the 13 industrial areas. Nevertheless, the report states that the use of AI in travel and tourism is currently in a minor stage, but has high potential for development.

AI in the hospitality industry can exert its influence from the tourist’s travel design to exploration, selection, reservation, and tourism experience [10]. Typical services include chatbot, service robot, travel assistant, product recommendation, prediction system, and service personalization [11]. In addition to hotels, restaurants, events, and travel agencies are actively embracing and using technologies, such as service automation and robots, starting with kiosks [12].
2.2. Chatbot

A chatbot is an automated system that emulates person-to-person dialogue through text or voice messages. The first chatbot is ELIZA, which MIT professor Joseph Weizenbaum developed in 1966. In the beginning, the conversation was conducted by matching the pattern recognition of sentences with corresponding answers. It develops into a chatbot that is easier for users to use through natural language processing (NLP) in the course of learning from AI.

The chatbot market has been revitalized as the entry barrier to the actual use of a chatbot has been lowered. A chatbot has become a major social issue as companies want to provide bot-enabled services to users. From its first appearance to the early 2000s, a chatbot used to simulate counselling and psychological treatment for users. Later, when smartphone penetration was activated, voice-based chatbot of global companies, such as Google, Microsoft and Amazon, began to emerge, starting with Apple’s Siri in 2010. Meanwhile, with the technological leap forward in chatbot design taking place in 2016, interest in a chatbot and utilization for business has begun to increase.

The benefits and costs of introducing robots, AI, and service automation in the hospitality industry were divided into monetary and non-monetary standards [12]. According to this research, a chatbot can make a labor-cost saving, quick response to a customer’s request. A chatbot, however, may generate additional costs, such as installation or maintenance, and may cause employees or customers to complain about imperfect services. Michaud [13] outlined the benefits of using a chatbot and proposed measures to increase their efficiency. Tussyadiah and Miller [14] emphasized the existence of chatbots in the hospitality industry, not only the economic benefits but also benefits in regard to socializing with customers, emphasizing their function as new sustainable service resources through personal data utilization, consistent service, and learning. Ivanov [15] presented the case of using a chatbot in tourism and discussed the limitations and cost aspects of chatbot utilization. Research on the technical aspects of chatbots presented basic principles and design methods that should be considered when introducing a chatbot, and reviewed the case of Watson chatbot application [16]. Atiyah, et al. [17] suggested a direction for enhancing the effectiveness of chatbots that combine existing algorithms. Meanwhile, a study of chatbot users proved through experimental design that the feeling that one is speaking with a person while using a chatbot depending on the type of sentence chatbot can be present [18]. It also verified through empirical analysis the improvement of a hotel organization’s performance, which can be brought by the introduction of chatbots [19]. Melián-González, et al. [20] explored positive and negative factors on the use of a chatbot through empirical analysis for users who used a chatbot while traveling. According to his research, communication discomfort in using a chatbot has a negative effect on chatbots usage intention.

As mentioned earlier, the services with AI may seem to provide only incomplete interactions with customers. For example, AI may not provide a complete service or meet customer expectations [21]. In addition, mechanical failure may prevent the service process from being completed. Nevertheless, the existing research on applying AI and chatbot to the hospitality industry does not discuss such service failures. Therefore, this study is intended to study the failure of AI in the hospitality industry and the resulting customer awareness and behavioral intention.

2.3. Service Failure

Service failure refers to when something goes wrong with a delivery process or outcome of a service. This means that the delivery of the service is located outside a customer’s perceived patience area, and the customer becomes dissatisfied [22]. Studies on the initial service failure attempted to identify the service failure situation using the ‘critical incident technique’ method [23]. Several researchers have used attribution theory, expectation disconfirmation theory, and justice theory in the empirical study to study the cause of service failure, the responsibility for failure, and the way of service recovery [24–26]. Since then, the studies of service failure have been expanded from offline to online. In addition, in the area of service encounters, research has been expanded to investigate service failures related to technology-related issues and self-service, as well as employees.
Applying technology in a service failure can take a different form than general employee service failures [27]. Failures in service provided by employees were rarely caused by customers. Therefore, in this type of service, much attention has been paid to the situation in which a failure occurs. However, when technology provides the service, a user’s characteristics appear to be an important variable because of the customer’s increased role [28]. Since the failure of SST can also be resolved through special procedures, studies have been conducted to distinguish the types of cooperative forms of problem-solving in this regard [29]. Subsequently, individual characteristics of the user become more important because the user may show a willingness to resolve the service himself.

If a technical failure or service failure of the robot, artificial intelligence, and service automation (RAISA) occurs in a service process, consumers may blame the company for failing to deliver the service rather than criticizing the RAISA or the technical aspects themselves. Therefore, from the service provider’s perspective, it is necessary to be cautious when using technical aspects to deliver a service [30]. Figure 1 shows the procedures for employee service failures and RAISA service failures. As seen in Figure 1, a number of technical support and methods to prevent failure have been studied since not only proper service recovery for technology-based service failures is difficult, but also the responsibility for failures occurring is unclear [31].

![Figure 1. Service failure of human and robot, artificial intelligence, and service automation (RAISA).](image)

Service failures and recovery studies in the hospitality industry have also been extensively studied because interactions and touchpoints with customers are more important in services in the hospitality industry than in general service-delivery situations [32]. In addition, the failure and recovery of services are important because they are intangible services provided by the hospitality industry, and both production and consumption can occur at the same time [33]. Further, much research has been applied to scenarios in the hospitality industry, such as hotels, airlines, and restaurants. Thus, it is important to study the failure of services in the hospitality industry at a time when AI technologies in the hospitality industry are integrated and are starting to deliver full-scale services to customers. Further, most studies have not discussed the service-failure situation of AI-applied services. In other words, no empirical study has been conducted on changes in users’ perceptions or behaviors in the face of actual AI service failures.
3. Research Model Development

3.1. Status Quo Bias Theory

We applied the Status Quo Bias Theory to see how people perceive differences in a technology applied to SST and AI in the hospitality industry. According to Samuelson and Zeckhauser [34], individuals making a decision tend to pick existing choices rather than new ones. This phenomenon is composed of rational calculations, cognitive errors, and psychological commitment. We do not discuss rational decision making because our study does not attempt to confirm the decision of service selection considering the functional merits between a chatbot and SST. Also, cognitive misperception is a comparison of loss and gain for the outcome of a choice, which our research does not discuss because we measure people’s perception of service.

Psychological commitment is explained by sunk costs and efforts to feel in control [35]. Sunk costs mean that people don’t easily change decisions in new ways, reflecting people’s investments in established means of decision making. This may also explain a preference for dealing with existing suppliers over new suppliers. Efforts to feel in control are explained by an individual’s desire to control a situation when a customer wishes to trade or use any service. In other words, people want to maintain the current situations because it is difficult for them to handle a situation in a new environment.

We believed that because SST services emerged a long time ago, many people would have learned about the use of SST by now. In addition, we assumed that SST’s successful service would be more positive for the attitude toward a hotel and revisit intention because it is easier for the user to control a situation in the SST than the AI service.

**H1.** If the service has been successful, according to the service delivery type (chatbot/SST), there will be statistically significant differences in consumers’ attitudes toward a hotel and revisit intention.

**H1a.** Compared to a chatbot, the success of SST services will give users a greater positive attitude toward a hotel.

**H1b.** Compared to a chatbot, the success of SST’s services will give users a greater revisit intention.

3.2. Service Failure and Customer Reaction

On the other hand, unlike successful service, failure of service puts a customer in an unexpected situation. Therefore, in order to clearly explore the customer’s perception of the service failure, we need to consider the customer’s propensity, the specific situation of a service failure, and so on [26]. In the meantime, the quality of service must be secured first in order to elicit customer satisfaction in the new technology environment [36]. If the service-delivery process is not properly equipped or the customer feels unfamiliar with the new technology, the customer’s perception of service failure is likely to be affected by the customer’s personal characteristics [37]. Bolton and Saxena-Iyer [38] said there is a difference between the degree of service failure and the degree to which customer complaints about the same service request, depending on a type of services. According to attribution theory, customers can feel less dissatisfied with the service provider when the cause of service failure comes from themselves. For example, Köcher and Paluch [39] presented the results of empirical analysis that customers respond more negatively to the failure of the full service than the failure of the self-service. Customers may think that their participation is higher in the service delivery process when using pad than when using a chatbot. Therefore, we assumed that when SST service fails, customers will respond less negatively. Accordingly, the following hypothesis was established.

**H2a.** Compared to a chatbot, the failure of SST services will give users a less negative attitude toward a hotel.

**H2b.** Compared to a chatbot, the failure of SST services will give users a less negative revisit intention.
3.3. User Characteristics

It is important to identify a user’s characteristics in determining how the failure of technology affects consumers. This is because, unlike the existing service-delivery process, technology service delivery has increased areas that consumers who use the technology have in the process, and thus, a consumer responsibility for service failures to be increased. When a service failure occurs, self-service technology users often blame themselves [28]. We applied user characteristics to this study with the concept of novelty-seeking and the need for interaction. The novelty-seeking of an individual is deeply related to innovativeness [40]. This may be linked to the user’s perception of the use of services with new technologies. The concept of the need for interaction can be connected with resistance to change or inertia from a certain perspective [41].

3.3.1. Novelty Seeking

Novelty can be defined as seeking a stimulus that is new, unfamiliar, and in a different way than before, or that comes from a challenging or adventurous temperament [40]. Man seeks novelty when the curiosity inherent in an individual is linked to a specific situation. This situation can be caused by information exploration, purchase of goods, seeking out unusual experiences, or selection of travel destinations [42]. On the other hand, in the case of usage of technology or systems, novelty could be caused by an individual’s innovativeness [43].

Many studies have considered novelty seeking as a personal trait in empirically studying technology acceptance and individual attitudes to technology. Dabholkar and Bagozzi [44] studied the influence of novelty on a relationship between characteristics of SST and attitudes toward technology use. In addition, the study was linked to various topics, such as online shopping [45] and mobile applications [46]. Flavíán, et al. [47] said that in order to explore a pure perception of people’s new technologies, it is necessary to check for novelty issues. Therefore, we have established the following hypothesis.

H3a. If the chatbot/SST service is successful, a high novelty-seeking group will have a more positive attitude toward a hotel.

H3b. If the chatbot/SST service is successful, a high novelty-seeking group will have a greater revisit intention.

3.3.2. Need for Interaction

In the context of service, need for interaction means that a customer needs an employee. The need for interaction is defined as the importance of an employee’s role in a service process that deals with customers who are not using technical help or self-service [44]. Kim, et al. [48] emphasized the importance of the need for interaction in the hospitality industry. Therefore, we adopted this instrument to understand how the failure of services through a chatbot or SST in a hotel will affect customers.

In existing SST studies, this variable has proven to have a negative effect on the user’s attitude or intent to use the technology. This can also be viewed in a context similar to technology avoidance. In other words, groups with a lower propensity to interact will prefer interactions with machines or technology. For these groups, if chatbot or SST fails to provide a service, it can have a greater negative emotion than on a group that needs more interaction with people. It could be possible to maintain a positive attitude and emotion against the service failure of technology if the variable of need for interaction has had a negative impact on technology-based services [49]. Thus, we assumed that when technology-based service failures occur, the groups with a lower need for interaction will have a more negative attitude and revisit intention.

H4a. If the chatbot/SST service fails, a group with a lower need for interaction will have a more negative attitude towards the hotel.

H4b. If the chatbot/SST service fails, a group with a lower need for interaction will have a lower revisit intention.
Based on the above hypotheses, we develop a research model shown in Figure 2.

Figure 2. Research model.

4. Methodology

4.1. Study Design

First of all, the service failure situation is a special situation for consumers. In order to participate in the questionnaire, recognition of the failure or success of a service situation must be preceded. Existing studies were conducted in the form of reminding the participants’ memories of service failures and recovery [50], or designing scenarios and assigning contexts. In this paper, we experimented with scenarios to find out the change of consumers’ perceptions and behavioral intentions, due to the failure of service providers. Scenario techniques can be used to relieve some of the memory recall issues that can occur when a person recalls the memory [51]. On the other hand, if the scenario presented the situation for AI application in the hospitality industry, which is still in its infancy, there may be limitations in role immersion because there may be a large number of customers who do not have sufficient experience. Therefore, in this study, participants direct their experience with the experimental chatbot, and SST developed by us in order to increase their understanding and realism of the scenarios. Through this, we intended to supplement the limitations of the service area where the consumer experience is insufficient. The scenario presented in this study is described in detail in Appendix A. Our scenario described the actual operational service delivery process in the hotel using a chatbot and in-room pad. In addition, the failure of the service was set as a technical problem in the delivery of the service rather than a resultant failure.

Through 2 (success/failure) × 2 (chatbot/SST), we have identified how people corresponding to each case react. Subjects were given a scenario of the service processing situation in the hotel and participated in the experiment. SST experiment setting through the use of pad in the room was done using google forms. In the case of the chatbot, it was developed for the purpose of research by using the Danbee platform (danbee.ai/).

4.2. Procedures

Experimental participants were randomly assigned to one of the four aforementioned hotel service conditions. Each scenario was based on actual services currently running in several hotels. The experimental procedures of this study are as follows. (1) Experimental participants are randomly assigned to one of the four situations. (2) Read the assigned scenario and request the service using a pad or chatbot. (3) After completing the delivery of the service, receive the final message and end the experiment. (4) Survey is conducted based on service delivery experience (Appendix B).
4.3. Manipulations and Research Instruments

Manipulation check items were used to check whether the respondents clearly recognized the failure or success of the situation from each experimental scenario. Specifically, we presented two questions to confirm the realism of the scenario [52]. In addition, two questions were presented to confirm how perfect the service delivery process was [53]. This study was able to confirm the respondents’ recognition of the service failure or success through a seven-point Likert scale (1—strongly disagree, 7—strongly agree).

All the items for constructs were measured using a seven-point Likert scale. Attitude toward hotel items was adapted from Bowen, et al. [54]. Revisit intention items were measured based on Van Vaerenbergh, Vermeir and Larivière [52]. Novelty seeking was measured by the items from Dabholkar and Bagozzi [44]. The 3-item scale for the need for interaction was adapted from Dabholkar [55]. The respondents rated their dissatisfaction on three-item developed by Li, et al. [56]. Items for negative word-of-mouth (WOM) intention were also derived from Li, Qiu, and Liu [56] partly. All the scales exhibited proper reliability as Cronbach’s alpha with a minimum value of 0.707, 0.762, respectively [57]. Detail instruments are shown in Appendix C.

4.4. Data Collection

We conducted a pilot test for the smart tourism research center students and researchers to detect possible program errors on chatbot and Google Forms. The main survey was conducted from 6 to 13 January 2020. Data were collected through the voluntary participation of students from the college of hotel and tourism management. Based on these, additional people who can follow the experimental process were recruited through snowball sampling. We explained the experiment procedure to participants briefly and informed that they could encounter a system error of the inability to move to the next step. We excluded some participants’ data who responded insincerely with a uniform answer to the whole questions or who recognized inaccurately to the content of the experiment. Finally, 161 data were used for the analysis. Table 1 shows the characteristics of the respondents.

Table 1. Demographic characteristics of respondents.

| Characteristics | Frequency | Percentage | Characteristics | Frequency | Percentage |
|-----------------|-----------|------------|-----------------|-----------|------------|
| Gender          |           |            | Occupation      |           |            |
| Male            | 62        | 38.5       | Civil servant   | 2         | 1.2        |
| Female          | 99        | 61.5       | Mechanic        | 8         | 5.0        |
| Under 20        | 5         | 3.1        | Office worker   | 51        | 31.7       |
| 20–29           | 82        | 50.9       | Business        | 7         | 4.3        |
| 30–39           | 45        | 28.0       | Professional    | 11        | 6.8        |
| 40–49           | 25        | 15.5       | Homemaker       | 1         | 0.6        |
| 50–59           | 4         | 2.5        | Services        | 26        | 16.1       |
| Less than 100 m w1 | 29   | 18.0       | Student         | 43        | 26.7       |
| 100–200 m w     | 30        | 18.6       | Other           | 11        | 6.8        |
| 200–300 m w     | 53        | 32.9       | Non             | 1         | 0.6        |
| 400–500 m w     | 7         | 4.3        | High school     | 7         | 4.3        |
| Over 500 m w    | 24        | 14.9       | In university   | 35        | 21.7       |
| Married         | 30        | 18.6       | University graduate | 67 | 41.6 |
| Single          | 128       | 79.5       | Graduate school | 52        | 32.3       |
| No response     | 3         | 1.9        | total           | 161       | 100.0      |

1 m won = million Korean Won.

5. Results

5.1. Manipulation Check

As a result of case-by-case data collection, 30 of the 36 data were used for successful service with a chatbot. For the failure with a chatbot, 45 of 79 data were used for the final analysis. A successful SST service used 46 data out of a total of 64 data, and failure 40 out of 62 data were adopted for final analysis.
Specifically, the data corresponding to the following three cases were removed. (1) Participants who were not immersed in the situation; (2) participants who could not finish the service delivery process to the end; (3) participants who did not respond after the experiment. It was recommended that all experimental conditions have at least 20 observations [58]. Our study derives statistical observations since all the cases of our study fulfill this criterion.

We checked the mean of the data to verify the validity of the data and analyzed the differences between groups to examine the hypothesis. For the statistical approach, analysis of variance (ANOVA), multivariate analysis of variance (MANOVA) and t-test were used in SPSS. As shown in Table 2, for the questions confirming the realism of the scenario, successful chatbots (M = 6.57), failure of a chatbot (M = 6.3), successful SST (M = 6.54) and failure of SST (M = 5.98) were high values in all cases. Thus, in all scenarios, we determined that respondents were engaged in the situation.

In the question of checking the service delivery status, successful cases were chatbot (M = 6.6) and SST (M = 6.73). On the other hand, the failure cases were chatbot (M = 2.09) and SST (M = 1.95). It was statistically significant difference in the case of chatbots (F (1, 73) = 307.91, p < 0.001), and also SST (F (1, 84) = 584.08, p < 0.001). Therefore, all experimental data showed that participants were well aware of and responded to the success and failure of the service.

### Table 2. Manipulation check.

| Question                                                | Chatbot (n = 75) | SST (n = 86) |
|---------------------------------------------------------|------------------|--------------|
| A given scenario can occur in real life.                |                  |              |
| It was easy imagining myself in the scenario situation. |                  |              |
| Average of the two items                                |                  |              |
| The service set up in the experiment was finally well completed. | 6.63 2.13 288.70*** | 6.72 2.15 359.03*** |
| I was able to complete the service request via chatbot/pad.| 6.57 2.04 260.19**  | 6.74 1.75 654.31*** |
| Average of the two items                                | 6.60 2.09 307.91**  | 6.73 1.95 584.08*** |

*p < 0.05, ** p < 0.01, *** p < 0.001. 1ANOVA is conducted to determine whether there are significant differences between situations.

5.2. Hypotheses Test

According to the manipulation check, we confirmed that the participants did not have any problem to play a role in the situations. Therefore, we analyzed the collected data and conducted hypothesis verification.

MANOVA was conducted to see if there was a significant mean difference between a chatbot and SST upon successful service. The test indicates significant difference between the chatbot and SST in the case of a successful service (Wilks’ lambda = 0.88, F = 4.79, p = 0.01). At the univariate level, the effect of service type is significant for attitude toward a hotel (F = 6.99, p < 0.01), revisit intention (F = 11.90, p < 0.01).

Attitude toward a hotel that succeeded using SST (M = 5.86) was higher than that of those who succeeded using chatbots (M = 5.01). Revisit intention with success of SST (M = 5.07) was higher than chatbot (M = 4.26). In H1a and H1b, we assumed that if the service was successful, the success of SST would have a greater attitude toward the hotel and revisit intention than the success of chatbots. Thus, H1a and H1b were supported.

In case of service failure, we suggested H2a and H2b verify the difference between a chatbot and SST with two dependent variables. According to the MANOVA, it indicates the non-significant statistical difference along with service types (Wilks’ lambda = 0.99, F = 0.28, p = 0.755). Specifically,
there was no statistically significant gap for the attitude toward a hotel ($M = 4.17$ vs. $4.19$) and revisit intention ($M = 3.81$ vs. $3.71$). Therefore, H2a and H2b were not supported. The MANOVA results are given in Table 3. The hypothesis test results according to the comparison between chatbot and SST are summarized in Table 4.

### Table 3. MANOVA results.

| Situation | Case          | Wilks' $\lambda$ | $F$-Value | df | $p$ | Situation | Case          | Wilks' $\lambda$ | $F$-Value | df | $p$ |
|-----------|---------------|------------------|-----------|----|-----|-----------|---------------|------------------|-----------|----|-----|
| Success   | Chatbot/SST   | 0.884            | 4.791     | 2.00 | 0.011 | Failure   | Chatbot/SST   | 0.993            | 0.281     | 2.00 | 0.755 |
|           | Dependent     |                  |           |     |     |           | Dependent     |                  |           |     |     |
|           | variables     |                  |           |     |     |           | variables     |                  |           |     |     |
|           | df            |                  |           |     |     |           | df            |                  |           |     |     |
|           | Sum of        |                  |           |     |     |           | Sum of        |                  |           |     |     |
|           | squares       |                  |           |     |     |           | squares       |                  |           |     |     |
|           | $F$           |                  |           |     |     |           | $F$           |                  |           |     |     |
|           | Sig           |                  |           |     |     |           | Sig           |                  |           |     |     |
| Success   | Attitude      | 1                | 12.933    | 6.990 | 0.010 | Failure   | Attitude      | 1                | 0.010    | 0.006 | 0.940 |
|           | toward a hotel|                  |           |     |     |           | toward a hotel|                  |           |     |     |
|           | Revisit       | 1                | 11.903    | 8.962 | 0.004 | intention| Revisit       | 1                | 0.204    | 0.118 | 0.732 |
|           | intention     |                  |           |     |     | intention|                |                  |           |     |     |

### Table 4. Hypotheses test.

| Hypotheses | Situation | Dependent variables | Type            | Mean (S.D.) | Results |
|------------|-----------|---------------------|-----------------|-------------|---------|
| H1a        | Success   | Attitude            | Chatbot (n = 30)| 5.01 (1.61) | Supported |
| H1b        | Success   | Revisit intention   | SST (n = 36)    | 5.86 (1.17) | Supported |
|            |           |                     | Chatbot (n = 30)| 4.26 (1.24) |         |
|            |           |                     | SST (n = 34)    | 5.07 (1.09) |         |
| H2a        | Failure   | Attitude            | Chatbot (n = 45)| 4.17 (1.52) | Rejected |
|            |           |                     | SST (n = 40)    | 4.19 (0.97) |         |
| H2c        | Failure   | Revisit intention   | Chatbot (n = 45)| 3.81 (1.39) | Rejected |
|            |           |                     | SST (n = 36)    | 3.72 (1.21) |         |

5.3. Group Comparison

We have identified how the individual’s degree of novelty seeking and the need for interaction may differ in the given situations. For this, each group was divided into low and high propensity groups based on the mean. The t-test was then conducted to analyze the mean difference between groups. We decided that it was reasonable to divide the group by the mean value because our study was following a normal distribution [59].

First, the difference of novelty seeking in the attitude toward a hotel according to the success of the service was significant only in chatbot ($t = 1.97, p = 0.059$). Specifically, the high group ($M = 5.64$) showed higher values than the low group ($M = 4.53$). The revisit intention of respondents was significantly different only in SST ($t = 3.13, p = 0.003$), in which case the high group ($M = 5.5$) was higher than the low group ($M = 4.59$). Thus, the hypotheses H3a and H3b, which would have a greater attitude and intention to return in the high-novelty group, were partially adopted. Figure 3 shows the t-test results with novelty in a successful service situation.

The results of the t-test after dividing the respondents’ need for interaction characteristics of service failures into high and low groups are as follows. First, in the attitude toward a hotel, the low group had a more negative attitude only in chatbot ($t = 2.91, p = 0.006$, high-NFI_M = 4.69, low-NFI_M = 3.45). As for the revisit intention, it was also confirmed that the lower group had a lower revisit intention only in the chatbot ($t = 2.47, p = 0.018$, high-NFI_M = 4.23, low-NFI_M = 3.24). The hypothesis test based on the t-test results is as follows. For both H4a and H4b, there was a significant difference between low and high groups regarding the need for interaction, but only when using the chatbot. As we assumed earlier, it has been shown that the group with lower values has a less positive attitude and also the revisit intention is lower. Therefore, we decided that H4a and H4b were adopted partially. Overall, the results of hypothesis verification through t-test according to the user characteristics of the chatbot and SST in successful and failed service situations are summarized in Table 5. Figure 4 shows the t-test results with the need for interaction in a failed-service situation.
Figure 3. T-test results with novelty in a successful service situation.

Table 5. T-test results.

| Hypotheses | Situation | Dependent Variables | Type   | Mean (Low Group) | Mean (High Group) | T-Value | Sig     | Results       |
|------------|-----------|---------------------|--------|-----------------|-------------------|---------|---------|---------------|
| H3a        | Success   | Attitude            | Chatbot| 4.53 (Low-novelty) | 5.64 (High-novelty)  | 1.967   | 0.059   | Partially supported |
|            |           | SST                 |        | 5.59 (Low-novelty) | 6.10 (High-novelty)  | 1.482   | 0.146   |                |
| H3b        | Success   | Revisit intention   | Chatbot| 4.23 (Low-novelty) | 4.28 (High-novelty)  | 0.101   | 0.920   | Partially supported |
|            |           | SST                 |        | 4.59 (Low-novelty) | 3.5 (High-novelty)   | 3.126   | 0.003   |                |
| H4a        | Failure   | Attitude            | Chatbot| 3.45 (Low-NFI)    | 4.69 (High-NFI)      | 2.907   | 0.006   | Partially supported |
|            |           | SST                 |        | 4.05 (Low-NFI)    | 4.45 (High-NFI)      | 1.048   | 0.309   |                |
| H4b        | Failure   | Revisit intention   | Chatbot| 3.24 (Low-NFI)    | 4.23 (High-NFI)      | 2.467   | 0.018   | Partially supported |
|            |           | SST                 |        | 3.68 (Low-NFI)    | 3.78 (High-NFI)      | 0.222   | 0.827   |                |

\(^1\) NFI = Need for interaction.

Figure 4. T-test results with the need for interaction in the situation of service failure.
5.4. Post Analysis

Based on the type of service, we conducted further analysis to explore meaningful outcomes in customer perceptions and behavioral intentions between service failures and service successes. Consumers who experience service failures may have complaints about the company, disseminate complaints to third parties, engage in online WOM activities, and have switching intentions [60]. Also, negative word-of-mouth often exerts greater influence than positive form [61]. In our study, we further examined the user’s dissatisfaction with the service and the degree of negative WOM intention. The information gain was employed to identify variables that could play an important role in each given situation.

Information gain (IG) is a measurement to represent the amount of information known from a random variable (X). In machine-learning research, this measurement is also known as Kullback-Leibler divergence emphasizing the conditional expected value of a given variable. In general, the information gain is calculated by the difference from the prior total entropy (T) and the current state by taking a new variable.

\[
IG(T, X_i) = E(T) - E(T, X_i)
\]

\[
E(T) = \sum_{i=1}^{c} -p_i \log_2 p_i
\]

\[
E(T, X_i) = \sum_{c \in X} P(c)E(c)
\]

In this Table 6, we can find that the dissatisfaction level (i.e., DISS) has the largest information gain (IG = 0.568) compared to the other information gain values, such as negative WOM (IG = 0.379) and revisit intention (IG = 0.052). From the result, we can notice that a low satisfaction level greatly explains the divergent of success and failure cases when a chatbot service is used. We find the same pattern in the self-service scenario adopting tablet interface (IG = 0.884 for dissatisfaction, IG = 0.554 for negative WOM and 0.146 for revisit intention). Important variables were identified based on information gain, and mean comparison was conducted to see if there was a significant difference among variables with service situations.

| Scenario | Information Gain |
|----------|------------------|
|          | Revisit Intention | Negative WOM | Dissatisfaction |
| Chatbot  | 0.568            | 0.379        | 0.052           |
| SST      | 0.884            | 0.554        | 0.146           |

In detail, mean comparison results, shown in Table 7, is describing differences. As we can notice, in the chatbot scenario, dissatisfaction (2.03 to 5.08, t-value = 10.085, p-value < 0.001), negative WOM (2.06 to 4.21, t-value = 7.037, p-value < 0.001) and revisit intention (4.26 to 3.81, t-value = -1.435, p-value = 0.156) are heading to more negative directions when a service ends in failure; however, it should be carefully noted that the revisit intention mean difference is not statistically significant. Meanwhile, the same pattern is observed in the self-service scenario in line with the information gain analysis; namely, the dissatisfaction (1.55 to 5.75, t-value = 23.157, p-value < 0.001), negative WOM (1.66 to 4.04, t-value = 8.915, p-value < 0.001) and revisit intention (5.07 to 3.72, t-value = -5.378, p-value < 0.001) all become negative when a service failed.
### Table 7. Mean comparison result for each variable.

| Scenario | Situation | Dissatisfaction | Negative WOM | Revisit Intention |
|----------|-----------|-----------------|--------------|------------------|
|          | Mean      | T-Value         | Mean         | T-Value          | Mean            | T-Value        |
| Chatbot  | Failure   | 3.81            | -1.435       | 4.21             | 7.037***        | 5.08           | 10.085***      |
|          | Success   | 4.26            | 2.06         | 2.03             | 2.06            | 2.03           |
| SST      | Failure   | 3.72            | -5.378***    | 4.04             | 8.915***        | 5.75           | 23.157***      |
|          | Success   | 5.07            | -5.378***    | 1.66             | 8.915***        | 1.55           | 23.157***      |

Statistical significance is marked as followed: *p*-value < 0.001 ***, *p*-value < 0.01 *, *p*-value < 0.05 * and no marker otherwise.

### 6. Discussion

An empirical study was conducted to analyze the importance of service type and service situation in the design of the hotel industry. The MANOVA with service type (chatbot/pad) and service situation (success/fail) on the impact of customers’ perceptions (attitudes) and behavior intentions (revisit intentions) was examined. In a successful service situation, customers have a more positive attitude toward a hotel and greater revisit intention, which can be explained by some aspect of the status quo bias theory. A failure situation, however, there is no significant differences for customers’ attitude and revisit intention.

The present study is suggested in comparison with established research as follows. According to the Oh, et al. [62], if someone can control a service situation, he or she feels more perceived usefulness and is more likely to use SST. Consumers who feel they have more control over the SST than the chatbot’s services, feel a more positive perception toward SST services [63]. These results suggest that the psychological commitment presented in the Status Quo Bias Theory is also applied to our research [35]. That is, in the situation of successful service, attitude and revisit intention to hotels that are powered by SST (pad) was shown to be high.

In a failure situation, it was shown that there was no significant difference between chatbot and SST. We interpreted this as follows. According to the empirical results of Lee and Cranage [30], there was a difference in the overall blame of the customer between a service failure of the employee and the failure of the SST, but there was no statistically significant difference between the failure of the SST and the company’s policy. This means that there is no significant difference in customer reaction, depending on the failure of the technical and policy aspects provided by the company. Both the chatbot and the SST presented in our study are considered failures in the company’s technical aspects, so there is no significant difference in attitude toward a hotel and revisit intention. Therefore, it is necessary to compare the failure of AI service with the failure of employees.

In order to determine the impact of customers’ individual characteristics in our experiment, we set the hypotheses based on previous studies. For hypotheses test, we employed a t-test between the high-value group and low-value group. In the case of a successful service situation, groups with high novelty-seeking characteristics perceive higher values in attitude toward a hotel only in the case of chatbots. Whereas, about the revisit intention, only SST has higher values with the high novelty group (see also, Figure 3).

In many theories and studies, attitudes have been proven to be an important antecedent to intention [64]. A general attitude toward a particular phenomenon or object can lead to specific behavioral intentions [65]. We interpreted that the group with high novelty-seeking characteristics had a more positive attitude only in chatbot and a greater revisit intention only in SST, as follows. Unlike chatbot service, the SST we presented in the experiment provided services to customers in a tangible form (pad). Therefore, it seems to have shown a significant difference in behavior, a more specific concept than attitude while exerting a more practical influence on the customer. Also, the group with high novelty-seeking characteristics seems to have shown a more positive response with SST because there are not currently many hotels with pads in their rooms. This can be seen in a similar context in previous study results where novelty seeking can play an important role in an
individual’s interest, awareness, and intention to use a new gadget [66]. However, further research should be conducted on the fact that SST showed a significant difference—not in attitude, but only in behavioral intention.

On the other hand, attitudes toward a hotel differed in the success of the chatbot depending on the size of the novelty. Since the chatbot is not tangible, like a pad, it does not seem to have a significant effect on revisit intention. It can be interpreted that the high-novelty group has a positive attitude toward a hotel with a chatbot success because the chatbot is the most advanced type of service as a reservation channel compared with traditional ways like a reservation by phone, internet, visit, etc.

The difference in customer’s perception and behavioral intention, due to a need for interaction in the failed service situation, is as follows. For all variables, only significant differences were found in chatbot results. In addition, for all significant differences, the group with a low need for interaction was found to have relatively negative attitudes and low revisit intention. These consistent findings towards chatbot can be interpreted in the same context as studies exploring people’s perceptions of new information technologies, which show more complex and technology-related features should be noted than for users’ general demographic characteristics [67]. The findings can be interpreted in the same vein as previous findings that early adopters focus more on their abilities and beliefs than on external stimuli or press in their attitudes to new technologies [68].

Summing up the discussion above, customers showed a more positive attitude and behavior intention toward the services of pad-based SST in a successful service situation. This can be explained by status quo bias theory, which describes a person’s decision making.

In the context of successful service, the individual novelty-seeking variable was partially adopted. This suggests that variables, such as user novelty, interest, and innovativeness, play an important role in the new service experience. The variable of need for interaction for the service-failure situation presented a unified result, but only regarding the chatbot. This suggests that intervention by an employee is, so far, entirely required because the technology or machine itself is significantly less capable of recovering services against technology failure.

In addition, alternatives to service recovery, due to the service failure of SST have been made in several studies. In particular, offline-based SSTs may use other machines or users can participate in co-creation to improve their services. In the case of an AI’s service failure, however, employees’ involvement may be important because there has not been much research on recovery strategies and it is difficult for users to come forward and participate in service recovery. Moreover, as mentioned earlier regarding the difference in the chatbot results, the individual characteristics are seen to have more influence on the judgment of the situation, as customers are not yet familiar with AI-enabled hotel services implemented by chatbot or service robot.

According to service-failure and recovery literature in marketing, human efforts to rebalance justice should be carried out immediately; otherwise, a customer is likely to consider retaliation measurements [69]. Joireman, et al. [70] indicated that a customer who encounters a failed service can be found in three post hoc states: resulting emotion (i.e., anger), goals and cognitions (i.e., showing a desire to revenge), and resulting behavior (i.e., retaliatory behavior including switching a service provider). Our findings from post-analysis indicate that automatic and artificial intelligence services seem to follow the same states, in line with Joireman, Grégoire, Devezer and Tripp [70]. First, a customer feels uneasy about the service failure indicating a higher level of dissatisfaction. If we call this stage a tentative and short-term reaction, the increase of negative WOM intention is related to showing a desire for revenge by sharing bad experiences with the service situation. Finally, the customer can decide to switch service providers, which mean the level of revisit intention decreases.

In service recovery, human intervention is crucial since the company needs to understand why the customer is involved in service errors or difficulties with mitigating tensions [71]. It should be noted that a customer is a part of the service process, and therefore, that knowledge capability and physical availability influence the quality of service provision (Bitner et al., 1990). When a service process fails because of a lack of prior information about the service process, a human service provider can resolve
the problem by learning about the failure situation; this is a kind of communication for recovering justice (Bechwati & Morrin, 2003). If the recovery process is successfully carried out, the intention to distribute negative information and aggressive opinions online is likely to decrease [72].

In the analysis result, we notice that self-service is more sensitive to service revenge. In line with Dabholkar and Spaid [73], we think immediately fixing a failed service is crucial in the context of self-service using a Kiosk. Forbes (2008) argues that self-service technologies are inflexible since a customer should initially learn how to communicate with the service system without human help, and it is difficult to report errors precisely to technical support persons when a service process stops. Compared to a self-service Kiosk, chatbot service system adopts a natural communication mode (Meuter et al., 2000). Therefore, although it is not conclusive nor deterministic, we guess that chatbot has an advantage in terms of service recovery. We admit that further research efforts should be carried out to learn how and why the differences are made between chatbot and self-service.

7. Conclusions

Since studies of chatbots with service failure have been insufficient thus far, our study is meaningful in that it analyses the connection between service type and service situation. In particular, this study’s suggestion of which business strategies should be highlighted, in accordance with customers’ traits with technology, is noteworthy. Moreover, our research is significant because it is the first paper to empirically review chatbot’s service failures and user responses. Through further analysis, we were able to address not only customers’ reactions to AI-related service failures, but also guidelines that could help establish recovery strategies. As mentioned in the introduction, in line with the trend of expanding the scope of service operation by RAISA, there are many related services failures. Therefore, our research topic is appropriate and timely, and will remain good academic material for future studies on similar subjects.

Based on the foregoing, our research provides several theoretical implications. Our research contributes theoretically to service research in the hospitality industry by studying AI-enabled services in hotels. In order to verify the hypothesis through empirical research, we presented an experimental setting that reproduces the service situation in a hotel, contributing to the expansion of the hospitality-industry research area by confirming how situations in an actual service environment can be academically tested. Moreover, within the huge research area of service failure, we added the study of service failure implemented by technology and AI. Thus, our research is a combination of service failure research and AI research. In addition, our research contributes to the expansion of the scope of the theory by applying the status quo bias theory, which has been proposed with various research topics, to service research between SST and AI.

In practice, companies and practitioners who want to provide chatbot services in the hotel and hospitality industries can use our research to identify how chatbot services affect their customers compared to existing services. In addition, our research suggests to practitioners what customer characteristics should be considered to deliver more effective services. Likewise, through this study, practitioners can identify which parts of customers will be significantly affected when an AI service failure occurs. Finally, our research can be used as a basis for how practitioners and companies can formulate service-recovery strategies in response to service failures of AI and SST.

In spite of its implications, our study has some limitations as follows. First, through a scenario-based experiment, this study confirmed the response to the results of the participants’ experiment. Although appropriate data were used for empirical analysis by checking the manipulation of scenarios and experiments, gaps with actual situations may still exist. Therefore, in future research, it is necessary to study their perception for users who have actually experienced the hotel’s technology-based self-service and robots or chatbot. Second, this study established AI and SST being used in hotels, representing the chatbot and pad, respectively. However, the hotel’s technology-applied services are appearing in various ways, such as robots, automation systems and kiosks. Therefore, subsequent studies will require the study of AI or SST that customers can experience in a variety of
forms. Finally, we studied the characteristics of users in two ways: novelty, and the need for interaction. However, the various characteristics of people concerning technology have been used a lot in existing research. Further use of various personal characteristics about AI’s services in research could lead to more extensive research results.

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Appendix A

Scenario

Scenario A1. Chatbot Service Situation

[You are going to log on to the hotel website and book a hotel through the chatbot. This chatbot is a dedicated chatbot of the hotel you choose, and it is provided on the hotel’s official homepage. Set number of guests and check-in dates and check-out dates. And then, select the desired room type. Finally, please complete the delivery of the service contents and the reservation of the room through the chatbot.]

Scenario A2. Chatbot Service Failed

[In the final stage of the service process through chatbot, it failed to move on to the final stage. The same message has been repeated, and the service is shut down with an error message.]

Scenario A3. Self-Service Situation through a Pad

[You stayed one night at Kyung Hee Hotel. And you are going to take a taxi to the airport after you check out. Before you check out, you call a taxi through a pad placed in your room. You request a service by following the procedures in the taxi call menu provided by the pad. You finally finalize the service delivery through the pad.]

Scenario A4. Self-Service through a Pad Failed

[During the service process via pad, it is not completed in the last step. After repeating the same screen, an error message appears, and the service terminates.]
Appendix B

Figure A1. Experiment screens of the chatbot.

Figure A2. Experiment screens of SST.

Appendix C

Scale items

Attitude toward a hotel
Overall, staying at this hotel is a good idea.
The service of the hotel makes a good impression of the hotel.
I like the idea of staying at this hotel.

Dissatisfaction

Overall, I was not satisfied with the transaction through the chatbot.
The trading experience with the chatbot was not good.
Chatbot’s overall quality of service did not satisfy me.

Revisit intention
I will be visiting this hotel next time.
I will not consider any other hotel next time except for this one.
Revisiting this hotel for my next trip is a good idea.

Negative e-WOM
I will leave negative reviews online about the hotel’s chatbot service.
I will encourage my friends and relatives not to choose this service.
I will negatively criticize this service to my friends and relatives.

Novelty seeking
I am always seeking new ideas and experiences.
When things get boring, I like to find some new and unfamiliar experience.
I like to continually change activities.
I like to experience novelty and change in my daily routine.

Need for interaction
I like interacting with the person who provides the service.
It bothers me to use a machine when I could talk to a person instead.
Human contact in providing services makes the process enjoyable for the consumer.

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