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Use of a Robot and the Personalization of Information Provision in Tourism Marketing Promotions

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ABSTRACT

Although a framework for artificial empathy exists in marketing research, the marketing effects of artificial empathy when using robots and generative artificial intelligence (AI) have not been sufficiently verified. This study shows that in the promotion of tourism services, artificial empathy can be achieved through the use of robots and personalization of the way information is conveyed. We established and verified a research model based on the hypothesis that influences visit intention. When using personalized explanations with generative AI, artificial empathy had a statistically significant positive impact on visit intention through helpfulness and perceived connectedness. Merely using robots cannot influence the outcomes (visit intentions). However, even without changing the main promotional content, we can influence the outcomes by personalizing the presentation to match audience preferences.

Keywords: Artificial empathy, Helpfulness, Perceived connectedness, Visit intention, Robot, Generative AI

INTRODUCTION

In marketing, research on the effectiveness of advertising recommendations made by social media influencers is progressing. Media influencers build careers by accumulating expertise in specific domains. Social media influencers' information dissemination based on their own experiences may be trusted more by consumers than traditional celebrity endorsement advertisements. Information senders' credibility has been reported to positively impact marketing effectiveness, such as repurchase intention (Sokolova and Kefi, 2020; Schouten, Janssen, and Verspaget, 2020; Masuda, Han, and Lee, 2022).

However, with the recent development of robots and artificial intelligence (AI), research on the use of automation technology in marketing has begun to be reported (Hoyer et al., 2020). The use of robots in services, called service robots and chatbots, which are based on programming and interacting with customers, is increasing. Thus, the impact of AI technology on robots in service is significant for advancing automation through marketing.

Research has progressed from the perspective of artificial empathy through the use of robots and AI. Artificial empathy is a concept that describes human cognitive and emotional empathy in the design and implementation of AI agents; it measures how customers empathize with AI agents in response to automated technology and customer marketing communications (Liu-Thompkins, Okazaki, and Li, 2022). AI-enabled customer service agents can provide emotional and social customer interactions comparable to human agents (Liu-Thompkins, Okazaki, and Li, 2022).

Although a framework exists for artificial empathy in marketing research, the marketing effects of artificial empathy when using robots and generative AI have not been sufficiently verified. Many previous studies have analyzed the marketing effects of technology utilization based on descriptive scenarios, without using actual robots. In the context of using actual robots and owing to the variety of implementation methods, it is necessary to demonstrate the influence of the type of robot that provides information and the method of conveying that information on its marketing effectiveness.

In this study, we analyzed the influence of using robots and personalized information delivery methods on visitors' intention to promote tourism attraction. Specifically, we utilize Softbank Robotics' humanoid service robot Pepper (Pandey and Gelin, 2018), and personalize the way information is conveyed based on two dimensions: rational/emotional and casual/formal. We set up a research model based on the hypothesis that artificial empathy influences visit intentions through helpfulness and perceived connectedness. This model was verified based on the data collected in the experiment. This research will support more effective decision-making when formulating tourism/service promotions that utilize automation technology to clarify trends in visit intentions based on differences in the use of robots and the personalization of explanations by generative AI.

PRIOR RESEARCH AND HYPOTHESIS CONSTRUCTION

Research on the concept of artificial empathy is underway as a perspective for evaluating the use of technology in the marketing field (Liu-Thompkins, Okazaki, and Li, 2022). Artificial Empathy measures how customers empathize with AI agents in response to automated technology and customer marketing communications, and Artificial empathy is mainly composed of three concepts: Perspective-taking, Empathic concern, and Emotional contagion (Liu-Thompkins, Okazaki, and Li, 2022).

The roots of artificial empathy lie in interpersonal fields, such as clinical psychology, social psychology, and ethics (Yalcin and DiPaola, 2018). Empathy refers to the ability to sense, understand, and share others' thoughts and emotions (Wieseke et al., 2012). Empathy has been investigated in many marketing research contexts (Weißhaar and Huber, 2016; Wieseke et al., 2012).

Research on the effects of social relationships on influencer marketing is ongoing. In particular, research is being conducted on parasocial relationships (PSR), which are pseudo-human relationships formed between influencers and followers, even though there is no direct interaction. Various studies have reported that PSR has a positive impact on marketing outcomes such as repurchase intention in endorsement advertisements on social media (Masuda, Han, and Lee, 2022).

In this study, we developed hypotheses regarding visit intention as a promotion of tourism attractions based on the extant literature on artificial empathy, the helpfulness of AI agents, and social relationships/connectedness. Social relationships, such as the PSR formed by product buyers, influence future purchase intentions (Masuda, Han, and Lee, 2022). Therefore, we propose the following hypothesis. H1: Perceived connectedness with an AI agent positively influences the intention to visit a tourist attraction. Regarding helpfulness, it has been verified that the helpfulness of AI agents influences perceived connectedness (Okazaki, Nguyen, and Celiktutan, 2023). Therefore, we propose the following hypothesis. H2: Helpfulness of an AI agent is positively related to its perceived connectedness with the AI agent. Artificial empathy affects the helpfulness of AI agents (Okazaki, Nguyen, and Celiktutan, 2023). Therefore, we propose the following hypothesis. H3: Artificial empathy is positively related to the helpfulness of AI agents. These hypotheses are summarized in the research model shown in Figure 1.

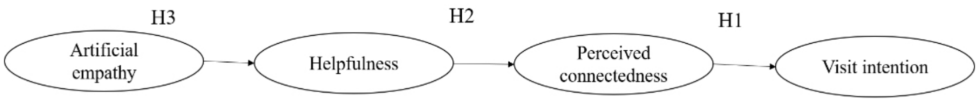

Figure 1: Proposed research model.

Methodology

In this study, we examined the influence of robot utilization and personalization of explanation phrases using generative AI on tourism promotion based on a proposed research model. To measure marketing effectiveness, we conducted controlled experiments using the following information provision methods: 1) neutral and standardized information with video and artificial narration as an AI agent (no-appearance); 2) personalized phrase of the explanation (main contents are same) with video and artificial narration as an AI agent (no-appearance); 3) neutral and standardized information with video and a robot as an AI agent; 4) personalized phrase of the explanation (main contents are same) with video and a robot as an AI agent.

Pepper (Pandey and Gelin, 2018) from SoftBank Robotics, was used. Pepper is a humanoid robot with a height of 120 cm that is capable of speech and gestures. As various reports have been made on the marketing effects of using pepper (Tuomi, Tussyadiah, and Hanna, 2021), we used pepper in this experiment based on its relationship with previous studies. In video-only explanations, audio files are incorporated into the videos. In the explanation using the robot, no audio was incorporated into the video and the robot spoke the same sentences. The audio in the video and the robot's audio were of the same type, and the timing of the audio explanations was aligned. To ensure that the robot naturally promoted the video, the robot spoke while facing forward. At the end of the sentence, the robot looked toward the screen where the video was playing (see Figure 2). On the robot's tablet, the information presentation was unified by presenting the robot's name tag "the explainer Laika."

The large language model (LLM) GPT-4 was used for personalization. In our study, we personalized PR texts along two dimensions, casual/formal and rational/emotional, resulting in four distinct PR styles: casual-rational, casual-emotional, formal-rational, and formal-emotional. To identify each participant's preferred PR style, we administered a pre-experiment questionnaire consisting of five questions. Each question contains four one-line PR texts representing different PR styles for the participants to choose from. Here, we prompted GPT-4 to generate one-line PR texts on predefined PR targets (products or services) for each PR style. Similarly, we used GPT-4 to generate personalized PR texts for each participant based on their preferred PR type (most chosen in the questionnaire). Here, GPT-4 is prompted to rewrite the original PR text into each of the four PR styles while ensuring the semantic invariance of the content. Finally, the automatically generated PR texts were checked by a native Japanese speaker to ensure their quality.

Figure 2: An experiment scene.

In this study, measurement items for each construct of the research model were adopted from extant literature and modified to suit the context of this study. Table 1 lists the measurement items used in the survey. All items were measured using a 5-point Likert scale ranging from "strongly disagree" to "strongly agree." In the experimental scenario, participants watched a one-minute promotional video of a tourist attraction in Kyoto, Japan, and then answered a questionnaire designed based on the research model. Artificial empathy was measured using six items (Davis, 1983; McBane, 1995). The helpfulness of the AI agent was measured using four items extracted from Okazaki, Nguyen, and Celiktutan (2023). Perceived connectedness was measured using five items (Okazaki, Nguyen, and Celiktutan, 2023). As an outcome of marketing effectiveness, visit intention was measured using two items from Tosun et al. (2015).

We constructed a web questionnaire based on the proposed research model and recruited participants for an experiment at a university in Kyoto, Japan. The experiment was conducted in December 2023, and 116 valid responses were received (Table 2).

We used structural equation modeling (PLS-SEM) based on partial least squares (PLS) to test our hypotheses. There are two types of structural equation modeling (SEM): covariance-based (CB) and PLS-SEM (Hair et al., 2019). PLS-SEM requires no assumptions about the distribution of the measured variables because its iterative algorithm is based on a series of least-squares fits, and allows robust estimation even with small sample sizes. Here, we use the PLS-SEM approach, which is more flexible with respect to the distribution of measured data and provides robust estimation results even when the sample size is limited.

Table 1. Questionnaire.

Construct	Item	Measure
Artificial empathy (Perspective-taking and Empathic concern)	PT1	The instructor (Laika) tried to understand the customer more deeply by imagining how things would look from the customer's perspective.
	PT2	The instructor (Laika) tried to "put himself in the customer's shoes"
	PT3	The instructor (Laika) tried to imagine how he would feel if he were in the customer's shoes.
	EC1	The instructor (Laika) sensed the customer's feelings.
	EC2	The instructor (Laika) showed concern about the customer's experience.
	EC3	The instructor (Laika) tried to make the customer feel better.
Helpfulness	Help1	The instructor (Laika) met my needs through its features.
	Help2	The instructor (Laika) provided good guidance (as needed) throughout the feature.
	Help3	The instructor (Laika) provided all the support I needed.
	Help4	The instructor (Laika) provided very wise and effective advice when needed.
Perceived connectedness	PC1	I felt a connection with the instructor (Laika)
	PC2	The explanations given by the instructor (Laika) deepened our bond.
	PC3	Connected with the instructor (Laika)
	PC4	The instructor (Laika) shared my interests and ideas.
	PC5	I felt a connection with the instructor (Laika)
Visit Intention	VI1	I would like to actually visit this tourist facility
	VI2	I will visit this tourist facility soon

Table 2. Respondent demography.

Characteristics	Frequency (n)	Percentage (%)
Gender		
Female	73	62.93
Male	43	37.07
Age group (years)		
<20	30	25.86
20-24	81	69.83
25-29	4	3.45
Unknown	1	0.86
Promotion category		
No robot + standard narration	26	22.41
No robot + personalized narration	31	26.72
With robot + standard narration	25	21.55
With robot + personalized narration	34	29.31

RESULT

As a step in the analysis, we performed structural equation analysis using PLS-SEM. In the first half of PLS-SEM, we evaluated the measurement model for constructs and question items. In the second half, we tested our hypotheses based on the proposed research model. Third, we compared the differences based on the results of each experimental group.

The measurement models in this model are reflective constructs (constructs that influence the measurement scale as latent variables). To evaluate the results of the reflective measurement model using all data (n = 116), outer loading, composite reliability, Cronbach's alpha, convergence using average variance extraction (AVE) (Table 3), and discriminant validity were performed (Hair et al., 2016). All the external loads on the components exceeded a threshold of 0.70, indicating that the index had a sufficient level of reliability. The composite reliability value was > 0.70, indicating a sufficient level of reliability. Furthermore, Cronbach's alpha was greater than 0.70, indicating that there was no problem in terms of reliability. The AVE exceeds the required threshold of 0.50 and has a high level of convergent validity. Regarding discriminant validity, all values were less than 0.9 according to the HTMT criteria, and discriminant validity was established.

Table 3. Reliability/validity analysis.

Construct	Item	Outer Loadings	Cronbach's Alpha	CR (rho_a)	CR (rho_c)	AVE
Artificial empathy	PT1	0.740	0.866	0.871	0.899	0.599
	PT2	0.832				
	PT3	0.766				
	EC1	0.813	0.788	0.813	0.875	0.701
	EC2	0.737				
	EC3	0.751				

(Continued)

Table 3. Continued

Construct	Item	Outer Loadings	Cronbach's Alpha	CR (rho_a)	CR (rho_c)	AVE
Helpfulness	Help1	0.798	0.815	0.837	0.876	0.640
	Help2	0.743				
	Help3	0.796				
	Help4	0.859				
Informative value	IV1	0.741	0.811	0.827	0.867	0.567
	IV2	0.849				
	IV3	0.691				
	IV4	0.785				
	IV5	0.688				
Perceived expertise	PE1	0.717	0.776	0.790	0.856	0.600
	PE2	0.709				
	PE3	0.787				
	PE4	0.874				
Perceived connectedness	PC1	0.789	0.873	0.875	0.909	0.666
	PC2	0.876				
	PC3	0.863				
	PC4	0.725				
	PC5	0.819				
Visit intention	VI1	0.849	0.670	0.677	0.858	0.751
	VI2	0.884				

Note: CR = composite reliability; AVE = average variance extracted

Table 4. R2, R2 adjusted, and Q2.

	R^2	R^2 adjusted	Item	Q^2predict
Visit intention	0.212	0.205	VI1	0.066
			VI2	0.055
Perceived connectedness	0.195	0.188	PC1	0.128
			PC2	0.142
			PC3	0.117
			PC4	0.143
			PC5	0.097
Helpfulness	0.322	0.316	Help1	0.171
			Help2	0.043
			Help3	0.188
			Help4	0.295

To evaluate the proposed research model, we evaluated the VIF, the significance of the path coefficient, the level of R^2 value, and the degree of predictive association Q^2 (Table 4). First, all VIF values related to the constructs are clearly below the threshold, and there is no problem of collinearity. Second, we checked the R^2 value of the endogenous latent variable. Third, when evaluating the significance of the coefficients, all paths were significant at the 0.001% level.

Table 5 shows the results of the path coefficients (H1-H3) for hypothesis verification. As a result of the analysis, all hypothesized paths were statistically significant.

Table 5. Hypothesis testing (H1 to H3) results (all data).

	Hypothesis/ Structural Path	B	p-Value	95% Confidence Interval	Result
H1	Perceived connectedness → Visit intention	0.460	0.000	[0.397, 0.728]	Accepted
H2	Helpfulness → Perceived connectedness	0.441	0.000	[0.205, 0.639]	Accepted
H3	Artificial empathy → Helpfulness	0.567	0.000	[0.311, 0.603]	Accepted

Each hypothesis was verified using a research model for the data from each experimental group. The results are summarized in Table 6. Regarding the groups, Group 1 pertains to neutral and standardized information with video and artificial narration as an AI agent (no-appearance); Group 2 refers to personalized phrases of the explanation (main contents are the same) with video and artificial narration as an AI agent (no-appearance); Group 3 pertains to neutral and standardized information with video and a robot as an AI agent; Group 4 refers to personalized phrases of the explanation (main contents is same) with video and a robot as an AI agent. For Groups 1 and 3, H2 became non-significant compared to the results of the overall data. In Groups 2 and 4, all paths were statistically significant for the overall data.

Table 6. Hypothesis testing (H1 to H3) results (data for each group).

	Group 1		Group 2		Group 3		Group 4	
Hypothesis	B	Result	B	Result	B	Result	B	Result
H1: Perceived connectedness → Visit intention	0.696***	A	0.618***	A	0.283	R	0.347*	A
H2: Helpfulness → Perceived connectedness	0.290	R	0.565***	A	0.665***	A	0.51***	A
H3: Artificial empathy → Helpfulness	0.597*	A	0.584**	A	0.547**	A	0.635***	A

Note1: Group 1 is neutral and standardized information with video and artificial narration as an AI agent (no-appearance); Group 2 is personalized phrase of the explanation (main contents is same) with video and artificial narration as an AI agent (no-appearance); Group 3 is neutral and standardized information with video and a robot as an AI agent; Group 4 is personalized phrase of the explanation (main contents is same) with video and a robot as an AI agent.; Two Tailed Test; *** Significance Level = 0.1%; ** Significance Level = 1%; * Significance Level = 5%; A=Accepted; R=Rejected

DISCUSSION

The main finding of this study was that in the group that used personalized explanations by generative AI, artificial empathy had a statistically significant positive impact on visit intention through helpfulness and perceived connectedness. Second, in the group that used neutral, standardized information, artificial empathy did not have a statistically significant positive effect on visit intention through helpfulness or perceived connectedness. In particular, in the standardized information provision group 1, which did not use the robot, the path from helpfulness to perceived connectedness was not statistically significant, whereas in group 3, the path from perceived connectedness to visit intention was not statistically significant.

The novelty of this research is that, in the case of standardized information provision, it is not possible to influence the outcome (visit intention) simply by using videos with artificial narration or a robot with artificial narration. We showed that by personalizing the explanation provision phrase to match the audience's preferences (e.g., rational/formal and casual/emotional), artificial empathy can also affect outcomes when using artificial narration or robots.

The theoretical implication of this study is that it provides a perspective for extending the theory of artificial empathy to the point where marketing outcomes can be obtained by combining artificial voices, robots, and explanations of personalized phrases against audiences.

Regarding the limitation, this time data were obtained on the respondents' general openness to interacting with technology and/or robots, but this was not reflected in the results of the analysis. The differences may arise from the degree of technology preference. Another limitation is that it was not possible to explicitly analyze the marketing effects of robots. Further research is required to analyze the effects of interactions with robots and personalization using generative AI. This will enable the construction of theories and verifications that will contribute to effective promotional decision-making using service robots and generative AI.

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