Consumer Evaluation of Hotel Service Robots[1]

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Abstract

In light of the trend in integrating artificial intelligence and robotics into tourism and hospitality operations, it is important to understand consumer responses to hotel service robots. Two studies were conducted to achieve this objective: an online survey and a laboratory experiment using measurements of automatic emotional reactions via biosensors. Responses to two types of robots, NAO for check-in and Relay for room delivery, were tested. Study 1 demonstrates that consumer intention to adopt hotel service robots is influenced by human-robot interaction dimensions of anthropomorphism, perceived intelligence, and perceived security. Differences were found between NAO and Relay: NAO's adoption depends on anthropomorphism and perceived security, while Relay's on perceived intelligence and importance of service operation in hotel experiences. Study 2 revealed support for the importance of anthropomorphism and perceived security in NAO, as reflected in galvanic skin response (GSR) peaks during sequences of interactions and fixation on NAO's face. Support for perceived intelligence in Relay was also identified. Implications for the hospitality industry are provided.

Keywords: service robot, human-robot interaction, godspeed scale, hotel management, emotional response, biometric research

1 Introduction

The topic of artificial intelligence (AI) and robotics seems to dominate recent debates in academic literature and popular media around the next technology applications to proliferate and greatly impact the service sector, including tourism and hospitality (e.g., Murphy, Hofacker, & Gretzel, 2017; Osawa et al., 2017). Automation has been implemented in service settings for some time (e.g., self-service kiosks) and the development of robots for the service sector has started decades ago (Borsenik, 1993; Collier, 1983). However, with recent technological advancements in AI and robotics, we see more and more service robots entering the realms of tourism and hospitality operations, including consumer-facing ones (Ivanov, Webster, & Berezina, 2017). Hilton Worldwide, in collaboration with IBM, piloted the world's first robot concierge (using Softbank's NAO robot) that draws knowledge from Watson and WayBlazer (AI systems) to inform guests on local attractions, restaurants, hotel amenities, etc. (Hilton, 2016). Starwood introduced robotic butlers (using Savioke's Relay robot) at their Aloft Hotel, mainly to deliver amenities to guestrooms in lieu of an actual human staff (Crook, 2014). In the name of efficiency, Henn-na Hotel was the first hotel to employ

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robots throughout its entire operations, from check-in at the front desk to automated luggage delivery and in-room companion (Guardian, 2015). The implementation of hotel robotics is often integrated with other enabling technologies such as facial recognition, automatic payment, drone delivery, and self-driving cars.

For hotels, efficiency of activities performed by staff is measured by the time needed to execute them; the less time, the less expensive labour cost would be. Hence, investment in robot labour is often less expensive than paying humans (Osawa et al., 2017). However, the adoption of service robots changes the nature of service experience as some service encounters are redefined by human-robot interaction (HRI). Different from industrial robots whose performance metrics solely depend on efficiency, the success of service robots depends on the satisfaction of the users (Bartneck et al., 2009a; 2009b). Therefore, it is important to understand the characteristics of robots that induce positive reactions from consumers in service settings such as hotels. The aims of this research are: (1) to understand consumer evaluation of hotel service robots and its effects on adoption intention, and (2) to identify if consumers react differently to different types of hotel service robots (i.e., NAO vs Relay) in light of their operational capabilities (i.e., check-in vs room delivery). In order to achieve these goals, two studies were conducted: (1) self-report measures of robot evaluation collected via a large-scale online survey and (2) psychophysiological measurements of automatic emotional reactions to robots collected using biosensor equipment. These two studies followed a concurrent nested (embedded) design, where the latter is used to complement and corroborate the findings of the former.

2 Human-Robot Interaction in Service

In light of the substantial impact potentials of autonomous robots on society, researchers have paid more attention to HRI. Compared to automated machines, robots are mobile and of a greater degree of embodiment, in order to fulfil their social and operational functions (Salem et al., 2015). The autonomy of a robot, which is its ability to accommodate variations of its environment (Stubbs, Hinds, & Wettergreen, 2007), intensifies its interactions with people (Thurn, 2004). This implies that robots get more empowerment, enabling them to make their own decisions in a wide range of circumstances. Thrun (2004) distinguished two types of HRI: direct and indirect interactions. The nature of HRI is closely associated with information flow (e.g., Duncan & Moriarty, 1998). Direct interaction exposes the bidirectional flow of information, which shows an equal footing between people and robots. Indirect interaction assumes a unidirectional communication whereby a robot acts on the basis of a command by an operator and responds back to its user.

Researchers have attempted to conceptualize and operationalize the different dimensions of HRI to explain user satisfaction with service robots (e.g., Bartnek et al., 2009a; 2009b). Humanoid robots have gained substantial attention due to the advantage of their appearance. In general, previous studies indicated that human appearance is more likely to induce positive perceptions and attitudes. That is, anthropomorphism (i.e., attribution of human characteristics to nonhuman objects) enhances a sense of efficacy with nonhuman objects as well as amplifies emotional attachment with them (Kiesler & Goetz 2002). Scholars in cognitive psychology suggested that perceived similarity between human behaviour and nonhuman movement of objects enhances accessibility of human schema (Morewedge, Preston, & Wegner, 2007). Anthropomorphizing products and brands, thus, can facilitate consumers to feel a congruency between human schema and the product features due to the human metaphor arising from the human-like objects (Aggarwal & McGill, 2007). Therefore, humanoid form of robots has traditionally been seen as the obvious strategy for successfully integrating robots into service/social environments (Duffy, 2003).

Animacy is another characteristic that robotics researchers aim for when designing robots. Robots that are lifelike can deeply involve users emotionally, which, in turn, will influence their behaviour (Scholl & Tremoulet, 2000). As robots can demonstrate physical behaviour, reactions to stimuli, and language skills (Bartneck et al., 2009b), they can be perceived as lifelike to a certain degree. More importantly, robots designed to interact with people in socially meaningful ways (such as service robots) are suggested to demonstrate a certain extent of personality (Lee et al., 2006). Moreover, people typically form first impressions when encountering others and positive first impressions often lead to positive evaluation. Therefore, the degree to which a service/social robot is liked by consumers (i.e., likeability) influences consumer judgment toward the robot (Bartneck et al., 2009b). Finally, perceived intelligence of robots (referring to the perceived ability of the robots to acquire and apply knowledge and skills in various service environment) and perceived safety (referring to the user's perception of the level of danger/hazard and of comfort) when interacting with service robots have been suggested critical in acceptance of robots (Bartneck et al., 2009a; 2009b).

3 Study 1: Evaluation of Hotel Service Robots

3.1 Methodology

In order to achieve the research goals, a questionnaire was developed to gauge consumer evaluation of two different hotel service robots: NAO and Relay. Respondents were randomly assigned to two stimuli and presented with an image of the robot and a video depicting the robot at work: NAO serving a female guest to check-in at the front desk (using the first scenario in EARS video; EARS, 2015) and Relay delivering snacks to a guestroom (Engadget, 2014). Respondents were then asked to complete the Godspeed Questionnaire (Bartneck et al., 2009a; 2009b), which consists of five parts: anthropomorphism, animacy, likeability, perceived intelligence, and perceived security. All scales were measured by 5-point semantic differentials; for example, *Fake–Natural*, *Machinelike–Humanlike*, and *Artificial–Lifelike*. Then, they were asked to indicate how important check-in or room delivery is for their hotel experience and state their intention to use the robot in the future. The questionnaire was distributed via a global market research company targeting consumers in the United Kingdom (UK) and United States (US) in August 2017. A total of 841 responses were collected, comprising of 51.8% US and 48.2% UK consumers. Of them, 53% are male and 65% are between 25 and 54 years old. Over 70% of respondents had 2-year college degree or above. About 55% of them have a combined annual household income below $60,000.

A partial least square (PLS) analysis was used to analyse the data. PLS is a proper method to address the purposes of this research. Given the limited extant studies that investigate the influences of robots on guest experiences in tourism and hospitality, the philosophical goal of this research is exploratory (or an extension of existing structural theory) rather than theory testing or confirmation (Hair, Ringle, & Sarstedt, 2011). In this vein, PLS allows identifying exogenous factors related to evaluation of robots to better understand an endogenous construct, adoption intention. Next, a multi-group analysis was conducted to indicate responses toward NAO and Relay robots.

3.2 Results

First, confirmatory factor analysis was run using SmartPLS 3.0. It was observed that item loadings of all latent constructs are over 0.60. Table 1 presents the result of the latent correlation analysis to test construct validity. It reveals that the square roots of average variance extracted (AVEs) of individual reflective constructs are higher than inter-correlations to other constructs, which confirms discriminant validity. The square roots of AVEs of individual constructs are also over or close to 0.80. It implies that each of the latent variables explains its indicators more than the error variances, supporting a notion of convergent validity. Then, two types of reliability estimations (Cronbach's alpha and composite reliability) consistently show reasonable levels (over 0.75) (see Table 1).

Table 1. Discriminant Validity

Measurement Items	CA	CR	AVE	Fornell-Larcker Criterion					
				AT	AN	LK	PI	PS	IM
AT: Anthropomorphism	.835	.881	.598	.773					
AN: Animacy	.851	.895	.632	.707	.795				
LK: Likeability	.943	.944	.815	.517	.726	.903			
PI: Perceived Intelligence	.907	.908	.729	.473	.672	.710	.854		
PS: Perceived Security	.779	.822	.702	.447	.562	.681	.640	.838	
IM: Importance	1	1	1	.247	.297	.241	.213	.215	1
IN: Intention	1	1	1	.403	.414	.422	.447	.440	.112

Note: CA = Cronbach's Alpha; CR = Composite Reliability; AVE = Average Variance Extracted

Next, the structural model was tested to estimate the proposed relationships by applying a bootstrapping random sampling approach (2,000 sample). As shown at Fig. 1, anthropomorphism (b = 0.205, $p < 0.001$), perceived intelligence (b = 0.196, $p < 0.001$), and perceived security (b = 0.194, $p < 0.001$) have statistically positive influences on adoption intention. These estimated factors explained approximately 27% of variances of the adoption intention.

In order to address the second objective, a multi-group analysis comparing path coefficients between those respondents who have been exposed to two different robots: NAO (n = 421) or Relay (n = 420), was conducted. Specifically, respondents exposed to NAO considered anthropomorphism (b = 0.235, $p < 0.001$) and perceived safety (b = 0.259, $p < 0.001$) as important elements affecting intention. In contrary, those exposed to Relay indicate that the two elements of anthropomorphism (b = 0.094, $p > 0.05$) and security (b = 0.055, $p > 0.05$) are not significant to induce the adoption intention. More interestingly, importance of operations (b = 0.113, $p < 0.05$) and perceived intelligence (b = 0.192, $p < 0.05$) appear to be vital factors affecting intention, in respect to a Relay robot. It is important to note that check-in was considered more critical than room delivery, with mean values of 3.64 and 2.66, respectively ($p < .001$). Adoption intention of Relay is higher than that of NAO (NAO = 2.98, Relay = 3.28; t = -3.59, $p < .001$).

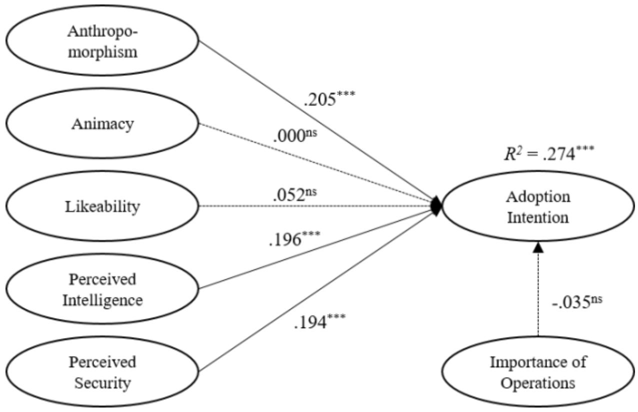


Fig. 1. Robot Evaluation on Adoption Intention

Lastly, a series of approaches to assessing confounding effects in the estimated results were taken into account. First, Harman's single-factor test was conducted by deriving single factors from exploratory factor analysis. The unrotated principal components analysis with seven factors counts for 40.795% of the total variance, below the cut-off value of 50%. Second, it was observed that no correlation shows an extreme value (r > 0.90). The collinearity test also reveals that the variance inflation factor values of all exogenous constructs are below 10, which suggests a limited concern of multicollinearity in the model.

4 Study 2: Automatic Emotional Responses to Hotel Service Robots

4.1 Methodology

To obtain better insights into consumers' inner states while viewing hotel service robots, Study 2 was conducted in a laboratory utilizing biosensor equipment: Tobii X2-30 eye tracker, Shimmer3 GSR+, and Affectiva AFFDEX facial coding system. Eye tracker measures gaze locations, time length of fixations, and pupil dilation, which are useful to assess attention and emotional state of respondents. GSR is a measure of skin conductance, which indicates the level of sweating at the skin's surface, signalling emotional arousal (e.g., stress, excitement, cognitive loads). The specific goal of GSR measurement is to identify skin conductance responses (SCR) that can be attributed to the stimuli. Heart rate (HR) and heart rate variation (HRV) were also measured, as accelerated heart rate can indicate emotional arousal. AFFDEX is an automated facial coding system consisting of face and facial landmark detection, face texture feature extraction, facial action classification, and emotion expression modelling (McDuff et al., 2016). The emotion expressions (joy, anger, surprise, fear, contempt, sadness, and disgust), valence, and emotional engagement were detected using EMFACS system (Brave & Nass, 2003) and given scores from 0 (absent) to 100 (present). The threshold for this research was set to 50. Together, these sensors provide a picture of the two dimensions in human emotions according to the circumplex model: valence and arousal (Russell, 1980; Russell & Feldman Barrett, 1999).

Respondents were invited to participate in the study through personal communication in a professional network setting. Fitted with biosensors, respondents went through a short calibration process before being exposed to the stimuli. This study uses the same stimuli and randomization procedure as in Study 1; respondents viewed the images for 8 seconds, the NAO check-in video for 77 seconds, and the Relay room delivery video for 98 seconds. The data collection and analysis were facilitated by iMotions biometric research platform for real-time synchronization of all complementary sensors. A total of 32 respondents participated in this study; 15 of them are male, 27 are in their 20s, and all reside in the UK.

4.2 Results

First, to better understand the objects that caught respondents' attention, eye tracking results were consulted. Fig. 2 presents gaze distribution for NAO and Relay robots. The heatmaps show the intensity of gaze, which is concentrated on the "face" of both robots (tablet-like screen in Relay) (A). Respondents also fixated on the "chest" area (text in Relay, to the right of chest) (B), and lower body (C). On average, respondents took 1.3 seconds (secs) to fixate on NAO's face (A) and spent 1.8 secs. In comparison, TTFF for the chest area (B) is 2.1 secs and time spent is .9 secs (C: TTFF = 3.4 secs, time spent = .3 secs). For Relay, the TTFF for A is 1.1 secs and time spent is 2.3 secs (B: TTFF = 1.4 secs, time spent = 1.1 secs; C: TTFF = 4.3 secs, time spent = .4 secs). These results indicate that humans are naturally drawn to "faces" first, indicating the importance of anthropomorphism in robot design, confirming results in Study 1 and in previous studies (Bartneck et al., 2009b). Also, respondents were drawn to text, as evident in longer time spent fixating on Relay's face and right chest. This may indicate higher cognitive load as respondents read the text. The same patterns were also found in the videos; respondents' gaze was concentrated on the face of one who was speaking during the conversation (examples of the video sequences with gaze distribution can be found in Fig. 6). NAO's hands move during a conversation so as to indicate animacy, mimicking natural human behaviour during a conversation. This, however, did not receive significant attention by respondents when compared to the face.

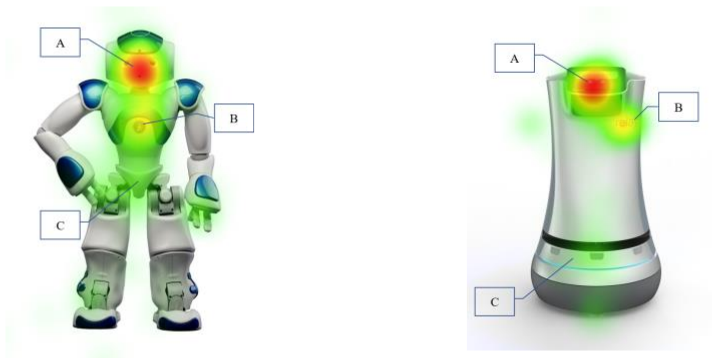


Fig. 2. Gaze Distribution and Area of Interest: NAO vs. Relay (Images)

Second, GSR, HR, and HRV were consulted to gauge emotional arousal levels. Fig. 3 illustrates the normalized GSR for NAO and Relay images (colours represent respondents). With the exception of a few with GSR following a downward trend without any peaks, respondents experienced GSR peaks during viewing NAO or Relay images. The share of respondents who had at least one GSR peak during viewing NAO was 73%, while Relay was 71%. The highest number of GSR peaks for NAO was five, while Relay was two. On average, NAO induced 8 peaks per minute (ppm) (net: 10.8 ppm), while Relay 6.3 ppm (net: 8.6 ppm). It is important to note that given the TTFF of 1.3 secs for NAO's face, it appears that most respondents experience an onset of GSR after fixating on the robot's face. GSR peaks on Relay are more spread out throughout the 8-second duration.

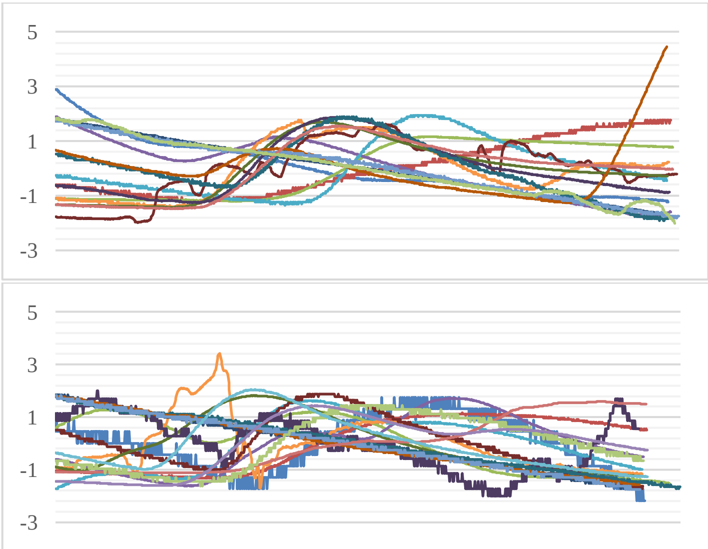


Fig. 3. Skin Conductance (Normalized GSR): NAO (top) vs. Relay (bottom)

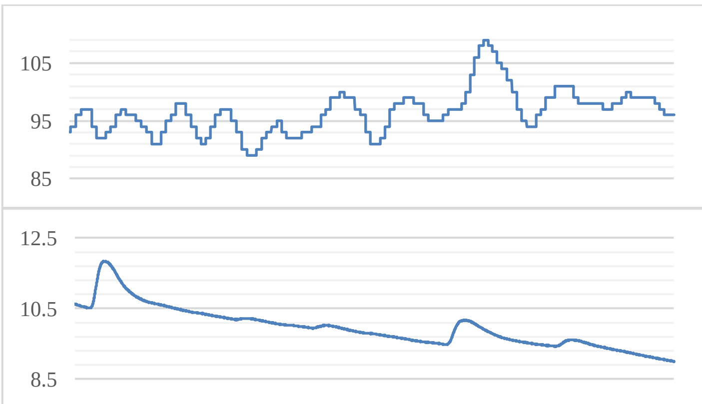


Fig. 4. Heart Rate (top) vs. Skin Conductance (bottom): Respondent #031

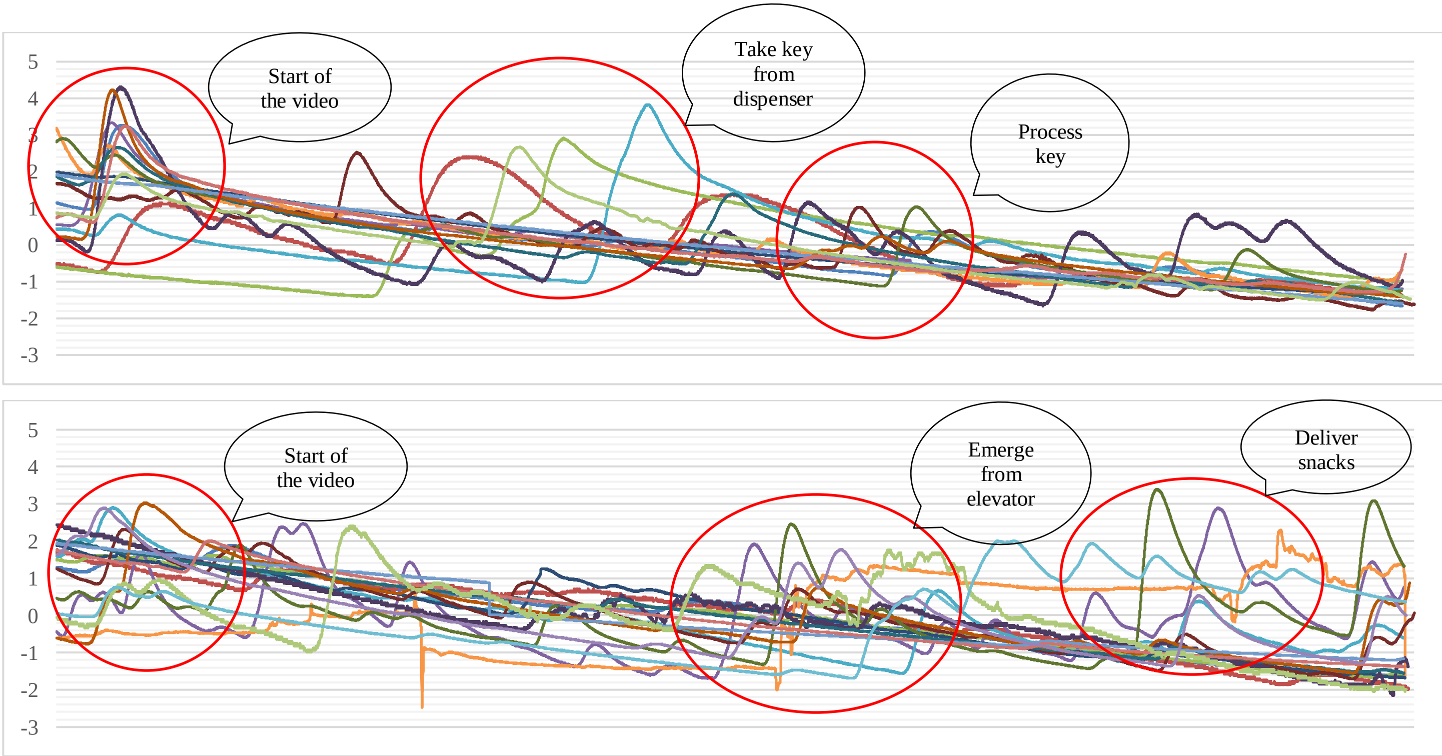
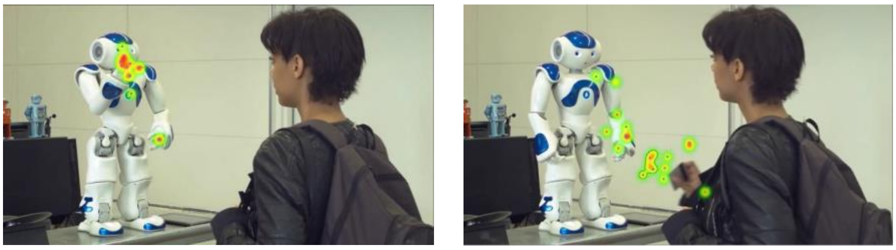


Fig. 5. Skin Conductance (Normalized GSR): NAO (top) vs. Relay (bottom)

In some instances, HR and HRV are consistent with GSR. However, as suggested in previous research, the impact of emotion on HR is less apparent than on GSR, as HR variability can be caused by sympathetic and parasympathetic nervous system and other mechanisms (Shimmer, 2015). Fig. 4 compares the HR and GSR from Respondent #031 who watched the NAO check-in video. While the HR is highly variable, a significant jump in HR at about two-third of the video is consistent with the peak in GSR. Due to high variability in respondents' HR, HR and HRV were consulted in this study only to complement the explanation for GSR peaks.

While watching the NAO check-in video, 87% respondents had at least one GSR peak; the highest number of GSR peaks was 12. All respondents (100%) had GSR peaks while watching the Relay video; the highest was 15. The NAO video induced 4.6 ppm on average (net: 5 ppm) and Relay 4 ppm, both higher than the typical rate of 1-3 ppm of non-specific skin conductance response (NS-SCR) (Dawson, Schell, & Filion, 2007). As illustrated in Fig. 5, GSR peaks can be attributed to several scenes in the videos. NAO is stationary; it stands on the desk and converses with the guest. Most peaks were detected at the beginning of the video, where NAO started greeting the guest. Other moments with significant peaks are when (a) NAO verifies guest's reservation and payment, and (b) asks guest to process the room key (i.e., to take a key from a dispenser and deposit it on a device located by NAO's side) (see Fig. 6). On the other hand, Relay is a mobile robot. In addition to the beginning of the video, significant peaks were detected along Relay's journey: taking the elevator, finding the room, serving the guest, being rated, and going back to the lobby.



(a) Verifying reservation and payment (b) Processing room key

Fig. 6. NAO Video Sequences with Most GSR Peaks (shown with gaze data)
(Video credit: EARS, 2015)

Lastly, to better understand the valence of respondents' emotions, results from facial expression analysis were consulted. While most respondents maintained neutral expressions throughout the study, some occurrences of positive and negative expression were detected (i.e., when the probability exceeds the threshold). Fig. 7 presents the share of respondents expressing valence, emotional engagement, and basic emotions while watching the videos. No indication of sadness or fear was detected. From the occurrences alone, it can be observed that more NAO respondents expressed positive emotions (including joy), while more emotional engagement was detected from Relay respondents. The share of respondents who expressed positive emotion is slightly higher in NAO than in Relay (20% and 18%, respectively), but lower in terms of negative emotion (Relay = 35% and NAO = 33%). However, in terms of time percent, on average Relay respondents had longer expressions of positive emotions (23.7% of the duration) than negative emotions (8.2%). On the other hand, the positive expression among NAO respondents lasted for 5.2% of the duration and the negative for 6%. When linked to other metrics (GSR peaks, HR, and eye tracking), it was identified that intense positive emotions (positive valence and joy) happened when Relay was navigating from the elevator and expressing happiness after being rated high for its service (making child-like, semi-circle movements and sounds). While this may be interpreted as indications of animacy, being able to navigate the hotel on its own signals its intelligence (Bartneck et al., 2009b), supporting Study 1.

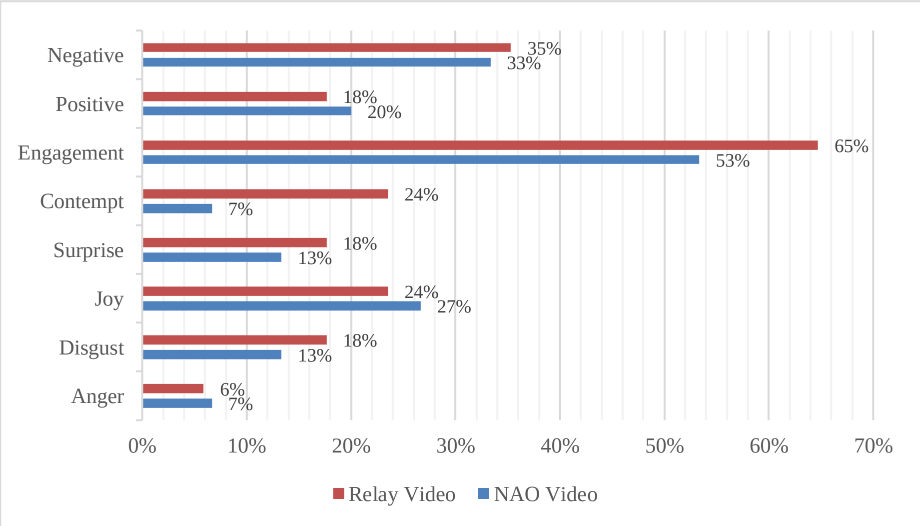


Fig. 7. Percent Occurrence of Emotional Expression: NAO vs. Relay

5 Conclusion and Implication

Study 1 found that adoption of hotel service robots is significantly influenced by dimensions of HRI: anthropomorphism, perceived intelligence, and perceived safety. Considering the functions of these robots, manning the front desk and delivering items to guestrooms, they are to replace human staff and interact with guests in a social setting (i.e., direct interaction during check-in and combination of direct and indirect interactions during room delivery). Therefore, the attribution of human characteristics and behaviour to robots that take the most human function is important. Indeed, anthropomorphism was significant in inducing use intention of NAO robot for check-in. This is supported by the findings in Study 2 where respondents' attention is focused on the face, with limited fixation on other body parts. Secondly, perceived safety was significant in affecting NAO's adoption. Based on GSR peaks and HR, it was identified that respondents experienced emotional arousals during the stages when NAO verifies reservation and payment and when it instructs the guest to process a room key. It can be suggested that consumers have a certain level of concerns over the safety of the check-in process as they anticipate its outcome.

On the other hand, Relay's adoption intention was significantly predicted by perceived intelligence and importance of operations. While the latter cannot be explained by Study 2, several emotional indicators hinted at perception of intelligence. For example, GSR peaks and attention were identified during critical moments when Relay is finding its way around, especially when it emerges from the elevator to navigate to the guestroom. This autonomous behaviour may be interpreted as intelligent behaviour by respondents (Bartneck et al., 2009b). It is critical to note that most respondents perceived that room delivery is not essential to hotel experience, when compared to check-in. As evident in lack of significance of perceived safety, people may feel more at ease about using robots for room delivery, as supported by the longer time share of positive emotional expressions for the duration of the Relay video.

By conducting two complementary studies, this research provides a better understanding of consumer evaluation of hotel service robots and its effects on adoption intention. Importantly, it provides empirical evidence supporting the critical factors that drive consumer adoption intention. For hotel managers, this research provides implications on the design requirements for employing robots. Firstly, for essential consumer-facing functions where consumers might be nervous about the outcomes of the interactions, it is important to enhance the feeling of safety. In addition, infusing the robots with humanlike characteristics (e.g., by programming humanlike expressions) will also contribute to inducing positive attitude from consumers. On the other hand, for non-essential service, it is important to pay more attention to functionality (e.g., robot delivery to find its way around, robot concierge to give relevant recommendations), one that will be interpreted by consumers as intelligence.

Due to limited access to hotel facilities employing actual robots, this study uses a second-hand interaction (i.e., respondents watch a video of a robot serving others). Therefore, HRI evaluation was not based on personal experience. However, the results are still significant to understand consumer openness to the emerging trends in hotel experience. Future studies should be conducted in actual service settings, using mobile eye tracker and other biosensors. Along with relatively low variance explained for behavioural intention, other factors related to adoption of new technology (e.g., trust, attitude, etc.) are suggested to consider in future research. Additionally, the videos used in this study are from two different sources: researchers (NAO) and marketers (Relay). Lastly, it is important to note that this study was not designed for experimentation with perfectly comparable situations. As robots are designed to fulfil certain functions (e.g., NAO cannot serve room delivery), comparing adoption intention between different types of robots and settings independent of the inherent design is not possible.

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