Do Travelers Trust Intelligent Service Robots?
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Highlights

- Trust in self-driving vehicles and robot bartenders was tested amongst travelers
- Negative attitude toward general technology negatively influences trust in robots
- Propensity to trust technology positively influences trust in intelligent robots
- Higher trusting beliefs lead to higher intention to adopt intelligent robots
- The physical form of robots does not affect trust

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Abstract

This research investigates travelers' trust in intelligent autonomous technologies based on two studies involving self-driving transportation and robot bartenders. Targeting travelers residing in the United States, online questionnaire was distributed to test the relationships between trusting beliefs in intelligent robots, its antecedents, and its outcomes. The results demonstrate that the cognitive trust formation process holds in situations involving intelligent robots as objects of trust. Trust in intelligent machines is influenced by negative attitude toward technology and propensity to trust technology. Surprisingly, the physical form of robots does not affect trust. Finally, trust leads to adoption intention in both studies. The contribution of this research is in elucidating consumer trust in intelligent robots designed for socially-driven interactions in travel settings.

Keywords: driverless car; self-driving vehicle; service robot; intelligent robot; robot bartender; initial trust formation

1. Introduction

As the travel and tourism industry continues to embrace radical technological innovation, we are witnessing the integration of artificial intelligence (AI) and robotics into the customer experiences in various settings (Murphy et al., 2017; Pan et al., 2015), including the accommodation and transportation sectors (Kuo, Chen, & Tseng, 2017; Tung & Law, 2017; Tussyadiah & Park, 2018). The cruise industry has started its service transformation by employing robots. Royal Caribbean equipped its four ships with the Bionic Bar, a bar manned by robotic bartenders able to take drink orders from passengers (Royal Caribbean, 2016). The same robotic bar system (called Makr Shakr) has been adopted in other establishments, including a bar located in Las Vegas' Miracle Miles Shops. Costa Cruise Line introduced a humanoid robot, Pepper, designed to recognize human emotions and proactively interact with the surrounding environment, to assist passengers with check-in information and on-board recommendation (SoftBank Robotics, n.d.). Finally, once regarded as futuristic, autonomous cars are becoming a reality (Walker, Stanton, & Young, 2001). In 2016, Uber added self-driving cars to its fleet, serving customers in Pittsburgh, United States (US) (Mitchell & Lien, 2016).

In tourism and hospitality settings characterized with intensive human contacts, replacing employees (humans) with robots (machines, intelligent agents) not only changes the nature of the service experience to include human–robot interactions, but may lead to a transformation in attitudinal and behavioral outcomes among customers (Pan et al., 2015; Thrun, 2004). While human–robot interactions has been an object of extensive studies as robots are increasingly prevalent in collaborative task-fulfilment settings, such as in integrative human–robot teams for manufacturing (Schaefer et al., 2012) and military operations (Billings et al., 2012), or in medical and assistive care services (Okamura et al., 2010; Wolbring and Yumakulov, 2014), it is a relatively novel area in the tourism domain (Ivanov, Webster, and Garenko, 2018; Murphy et al., 2017). Therefore, how consumers view, respond, and react to intelligent service robots remains important to explore to guarantee the successful application of robotics in various travel and tourism operations.

Literature in human–robot interactions has advocated the critical role of trust in influencing the overall acceptance and usage of autonomous technology (Tay et al., 2014; Yagoda and Gillan, 2012). For example, while consumers to interact with technological artefacts, Wang and Benbasat (2005) found that they need to place a significant level of trust in technology. Similarly, because robots are programmed to take the place of humans in situations involving various exchanges, consumers must be willing to take the risk of delegating responsibility for actions to the machines (McKnight, 2005; Yagoda and Gillan, 2012). Furthermore, as the requirements for robotic design expand to include socially-driven interactions with humans, such as those for robot bartenders (Foster et al., 2013; Giuliani et al., 2013), the role of human–robot trust in technology adoption becomes more prominent (Schaefer et al., 2012).

In examining trust in technology, research suggested several antecedent factors related to the characteristics of the users, the technologies, and the environment where the interactions happen. User-related antecedents of trust include propensity to trust in general technology (McKnight et al., 2011) and negative attitudes toward technology (Nomura et al., 2004; 2006; Wang et al., 2010). The physical form of robots was also proposed as an important antecedent of human–robot trust (Fong et al., 2003;

Hancock et al., 2011; Schaefer et al., 2012). For example, previous studies found that human-like robots (i.e., robots designed with technical anthropomorphism in mind) triggered significantly different reactions from users compared to machine-like robots, with robots capable of expressing human-like characteristics being considered more trustworthy (Fong et al., 2003; Haring et al., 2013). This suggests the tendency of users to develop trust when robot appearance matches the intended capabilities. In light of the different intelligent machines currently offered in the travel and hospitality sector (Ivanov, Webster, and Garenko, 2018), a better understanding on how consumers view and respond to service robots and autonomous vehicles will assist in better design and future applications of artificial intelligence and robotics. To that end, this research aims to investigate trust in intelligent robots in hospitality and tourism, its user-related antecedents, and its effects on trusting intention. To achieve this, two studies were conducted with different consumer-facing robotic applications and service settings: self-driving vehicles for on-demand transportation and robotic bartenders for cruise ship operations. For simplification purpose, the term intelligent robots will be used throughout the manuscript to represent the two intelligent, autonomous technology applications under study.

2. Trust in Intelligent Robots

Consumer trust for machines can be extended from interpersonal trust and influenced by similar factors that determine trust between people (Muir, 1994; Yagoda and Gillan, 2012). In interpersonal exchanges, trust can be understood as expectations of outcomes where statements, promises, and behavior of others can be relied upon (Koller, 1988; Luhmann, 1979; Rotter, 1967). This definition emphasizes that social exchanges are not devoid of ambiguity; that trustees have the freedom or volition to choose alternative behaviors that would generate negative consequences to trustors and that one resorts to trusting behaviors in order to engage in various social interactions despite the uncertainties of the outcomes (Beldad et al., 2010). Following this definition, trust in information technology is thus defined as a user's expectation that information technology artifacts such as websites, virtual peers, recommendation agents, automated online assistants, robots and the likes will fulfill the expected responsibilities. Furthermore, a user trusts information technology artifacts relatively to a goal, something he/she needs to achieve. Therefore, trust in technology is context-specific; it applies to a specific situation, but not necessarily to another (Castelfranchi and Falcone, 2001; O'Donovan and Smyth, 2005).

Trust reflects judgments that the trustees have suitable attributes for performing as expected. According to Beldad et al. (2010), trust is assessed as a product of users' capacity in evaluating the trustworthiness of information technology artifacts. Individuals use a set of criteria in order to arrive at a reliable assessment of trustworthiness. For interpersonal trust, these criteria include competence or ability, benevolence, and integrity (Mayer et al., 1995; McKnight et al., 1998; Morgan and Hunt, 1994). Ability refers to the expectation that trustees possess the necessary skills and abilities to fulfill the tasks; benevolence is the expectation that trustees have genuine concern for the wellbeing of trustors; integrity is the degree to which trustees are consistent, predictable, and reliable (Gefen, 2002; Mayer et al., 1995; McKnight, 2005; McKnight et al., 2011). These three dimensions are considered conceptually distinct (Kumar et al., 1995), but reflect a higher order expectation of trusting beliefs. These person-to-person trust dimensions have been successfully used to assess trust in technology (Gefen, 2002; Mayer et al., 1995; Wang and Benbasat, 2005), including in the fields of travel and tourism (Wang et al., 2014; 2015; Li et al., 2017).

However, McKnight et al. (2011) suggested a framework that differentiates trust in technology and interpersonal trust and developed the constructs and measures of trust that are more suitable to be applied in human–technology relations. They argue that while technology lacks volition or will, trustors still face uncertainty that technology may not complete expected obligations, intentionally or not. Further, while trust in technology primarily reflects trustors' expectation of the technology characteristics (e.g., what intelligent robots are designed for), trust in technology often reflects people's emotions toward technology, such as disappointment from interrupted goals/plans due to a service failure. Comparable to the criteria people use to assess trustworthiness in people, McKnight et al. (2011) conceptualized and verified three dimensions of technology trusting expectations: functionality, helpfulness, and reliability. Functionality refers to technology having the functions and features to accomplish intended tasks; helpfulness to technology providing adequate and responsive aid, and reliability to technology continuously operating properly and in a flawless manner (Lankton et al., 2014; McKnight et al., 2011; Thatcher et al., 2011). Therefore, trust in intelligent robots, which is a form of trusting beliefs in specific technology, is assessed in this study as a multidimensional factor consisting of functionality, helpfulness, and reliability. Following McKnight et al. (2011), these expectations are perceptual, instead of objective in nature.

2.2 Antecedents of trusting beliefs

Propensity to Trust. Several researchers suggested that trust in specific technology is influenced by users' propensity or disposition to trust (Gefen, 2002; Jarvenpaa et al., 1998; Mayer et al., 1995; McKnight et al., 1998). Merritt and Ilgen (2008) argued that "just like individuals have a general propensity to trust or distrust other people, they may have a propensity to trust or distrust machines" (pp. 195-196). By definition, propensity to trust is a consistent trusting tendency, which is neither trustee specific (as are trusting beliefs in intelligent robots), nor situation specific (as are trusting beliefs in bartending) (McKnight et al., 1998; McKnight et al., 2011). It indicates users' willingness to rely on a technology across a broad range of situations and information technology artifacts. It was identified that people with high propensity to trust predicted the trustworthiness of others better than those with low trusting propensity (Kikuchi et al., 1996). In e-commerce context, Salam et al. (2005) found that some customers are likely to trust anything or anyone, including trusting online vendors while having limited information about them. Empirical research has evidenced the positive effects of propensity to trust on trust formation in technology (Chen, 2006; Lee and Turban, 2001). Chen (2006) found a positive effect of disposition to trust on online trust during interaction with a travel website. Lee and Turban (2001) identified the moderating effects of propensity to trust on trust formation in the context of internet shopping. While empirical support for the link between propensity to trust in automation and human–robot trust is rather limited (Merritt and Ilgen, 2008; van den Brule et al., 2014), researchers have conceptualized that a general tendency to trust automation differs among users and is likely to affect trust in specific robots (Adams et al., 2003; Hancock et al., 2011a; 2011b; Lee and See, 2004).

Researchers differentiated propensity to trust into two constructs, namely faith in general technology and trusting stance (McKnight et al., 2011; McKnight et al., 2000). Faith in general technology, which refers to users' beliefs about attributes of technology in general (non-specific technology), is comparable to the concept behind faith in humanity, a belief that human beings (non-specific persons) are generally well-meaning and reliable (McKnight and Chervany, 2001-2002; McKnight et al., 1998). This suggests that users with higher faith in general technology expect technology to be reliable, functional, and helpful (McKnight et al., 2011). Based on calculative-based trust concept, trusting stance refers to users' tendency to believe that relying on technologies will generate positive outcomes (McKnight et al., 2011). Higher trusting stance means that users will likely use technology until given reasons not to. These two constructs have been identified as determinants of trust in previous studies (McKnight et al., 1998). Specifically, McKnight et al. (2011) found significant direct effects of faith in general technology and trusting stance on trusting beliefs in specific technology. Therefore, the following hypotheses are suggested:

Hypothesis 1. Faith in general technology has a positive effect on trusting beliefs in intelligent service robots.

Hypothesis 2. Trusting stance in general technology has a positive effect on trusting beliefs in intelligent service robots.

Negative Attitudes toward Robots. Previous studies have revealed that some consumers exhibit negative affective and attitudinal responses to novel technology. Researchers refer to it as technophobia, which explains people's fear or anxiety toward technologies (Brosnan, 1998; Rosen and Weil, 1990). This has been widely studied in cases of computerphobia, an anxious emotion that prevents people from using computers, particularly in the field of educational psychology. However, technophobia is believed to be widespread with other information technologies (Thatcher et al., 2011) and particularly relevant to explain people's apprehension to current technological trends, such as fear of intelligent robotic agents implemented in self-driving cars, drones, etc. (Dietterich and Horvitz, 2015). Technophobia can be defined as: "(a) anxiety about current or future interactions with computers or computer-related technology; (b) negative global attitudes about computers, their operation or their societal impact; and/or (c) specific negative cognitions or self-critical internal dialogues during actual computer interaction or when contemplating future computer interaction." (Rosen and Weil, 1990, p. 276).

Researchers have measured the general attitude toward technology using different scales; two of these are Nickell and Pinto's (1986) Computer Attitude Scale (CAS) and Nomura et al.'s (2006)

Negative Attitudes toward Robots Scale (NARS). CAS is a Likert scale devised to measure positive and negative attitudes toward computers in society and is suggested to have useful training applications in educational and industry environments where people perform their tasks with computers (Nickell & Pinto, 1986). Reliability and validity of CAS have been tested in various settings (see Kim, McLean, and Moon, 1994). In terms of factorial validity, studies found varying results, with the items of CAS forming one to eight factors. In a more recent study, Palaigeorgiou et al. (2005) developed a CAS specifically for computer science freshmen students, to include five factors such as hardware usage anxiety, fears and evaluation of negative and positive consequences of computer use in personal and social life. They also found that the predictive validity of the scale on computer use variables (e.g., intensity, breadth, knowledge) to be adequate.

As robots are becoming more commonplace in society, the roles of negative attitude toward robots have gained attention in human–robot interactions. Negative attitude toward robots is a psychological or mental state that prevents humans from interacting with robots in their daily life, thus prevents robots from being accepted by the masses (Nomura et al. 2004; 2005; 2006a; 2006b). Following a psychological definition, negative attitude toward robots is a relatively stable and enduring predisposition to respond negatively to robots in general (Nomura et al. 2006a). Similar to propensity to trust, Negative Attitude to Robots Scale (NARS), developed based on free-form responses from participants regarding anxieties towards robots (Nomura and Kanda, 2003), reflects consumers' global attitude toward robots. It can be suggested that negative attitude toward robots in general will affect trust in specific service robots, such as robot bartenders or delivery robots. Researchers have tested NARS in experiments involving different types of robots, including a humanoid communication robot called Robovie (Nomura, Kanda, and Suzuki, 2006), a robot pet, such as Sony's Aibo (Bartneck et al. 2007), and a mechanical robot, such as PeopleBot (Syrdal et al. 2009). These studies found that higher negative attitudes toward robots are associated with higher negative evaluations of robot behavior (Syrdal et al. 2007) and lead to avoidance behavior (Nomura et al. 2004; 2006a). Hence, the following hypothesis is suggested:

Hypothesis 3. Negative attitude toward robots has a negative effect on trusting beliefs in intelligent service robots.

Robot Form. It has been suggested that the characteristics of robots are important antecedents of human–robot trust. In fact, numerous researchers have attempted to classify robots into different categories (taxonomy) based on their attributes, both physically and in terms of its functional ability. For example, Fong, Nourbakhsh, and Dautenhahn (2002) classified socially-oriented robots into forms such as anthropomorphic (human-like), zoomorphic (animal-like), caricatured, and functional. Relying specifically on the physical forms, Volante et al. (2016) classified robots into anthropomorphic/machine-like, machine-like/industrial, and an ambiguous design. The foundation behind this taxonomy is that just as a cognitive mental representation of the partner's actions is crucial for successful coordination in human–human dyadic interactions, users develop trust in a robot if its appearance matches its intended capabilities. They found that simple spherical, ball-like robots were consistently selected by users to complete simple tasks, but not the more complicated, industrial-like robots (Volante et al. 2016). Further, researchers believe that humanoid robot is a more appropriate form for social robots, such as robot assistants, and implicitly assume that the robot head is the primary place of human–robot interactions (DiSalvo et al. 2002), just as the (human) face is important in human–human interactions. For robot bartenders, it can be suggested that the closer a robot appears to resemble humans, the more it would be trusted. That is, humanoid robots will be more likely to be trusted than the mechanical robots. Therefore, the following hypothesis is suggested:

Hypothesis 4. Robot form has an effect on trusting beliefs in intelligent service robots.

2.3 Outcome of trusting beliefs

Trust in robots is considered the main indicator of acceptance (Gaudiello et al. 2016). Lack of trust, consequently, is viewed as the main hurdle of automation in various strategic areas. In the field of tourism and hospitality management, the link between trust and technology adoption has been well-researched, even though the focus of these research has been primarily on websites and/or mobile applications (Agag and El-Masry 2016; Chen 2006; Wang et al. 2014; 2015). For example, Kim et al. (2011) identified the positive impact of trust on adoption of electronic commerce for tourism products and services. Chang et al. (2006) also found the positive role of trust in adoption of location-based services for tourism. Wang et al. (2014; 2015) attempted to conceptualize and measure eTrust (i.e., trust formed online) and identified the influence of hotel website's characteristics on trust formation. Further, they found that eTrust has a positive effect on online booking intention. Similar results were also confirmed in more recent studies by Li et al. (2017) on hotel websites and Agag and El-Masry (2016) on online travel websites. Finally, Morosan and DeFranco (2016) found the indirect effect of perceived security, which is associated with trust, on intention to use near field communication mobile payments in hotels.

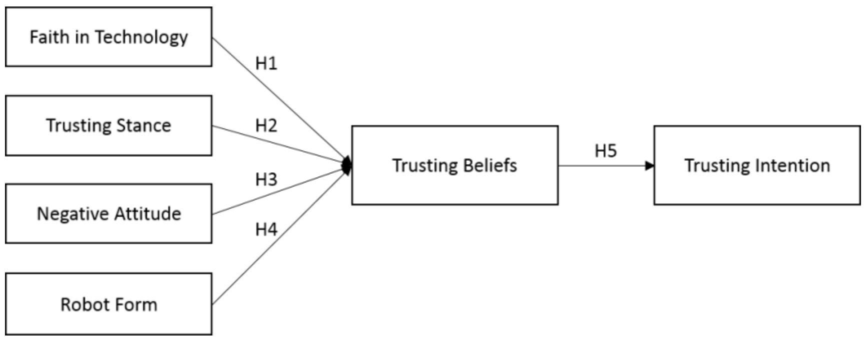
In marketing and information systems fields, the link between trusting belief and trusting intention (such as adoption or post-adoption behavioral intention) have been identified in various contexts involving automated technology. Pavlou and Gefen (2004) identified that trust in an online community of sellers influences intention to transact. Komiak and Benbasat (2006) identified the effects of cognitive and emotional trust on the intention to adopt a recommendation agent as a decision aid and a delegated agent. Indeed, deriving from the Theory of Reasoned Action (Fishbein and Ajzen 1975), Vance et al. (2008) advocated that "the process progressing from beliefs to behaviors has been found to be highly amenable to the formation of trust" (p. 76) and that the cognitive process of trust formation holds in situations where information technology artifacts are the objects of trust. Further, trusting beliefs in information technology artifacts were identified to strongly predict trusting intention (Vance et al. 2008). Drawing on the same theoretical groundworks, it can be suggested that trust in service robots positively affects behavioral intention to adopt and/or recommend services that utilize these robots. The following hypothesis is suggested:

Hypothesis 5. Trusting beliefs in intelligent service robots has a positive effect on trusting intention.

3 Research Framework and Methods

Based on the aforementioned literature and hypotheses, the conceptual model of trust in intelligent robots that guides this research is illustrated in Figure 1. Trusting beliefs in intelligent service robots consisting of expectations of functionality, helpfulness, and reliability of the robots (specific, local concept), is influenced by user-related antecedents, which include faith and trusting stance in general technology and negative attitude toward robots (general, global concept), and the appearance of the intelligent service robots (specific, local concept). The outcome of trusting beliefs is trusting intention. This model was tested in two studies of different robotic applications: self-driving vehicles for on-demand transportation and robotic bartenders for cruise ship operations. The studies employ the same methodological approach (quantitative data analysis on primary survey data). We first describe data collection and analysis as this covers both studies and below provide study-relevant measurement items and results separately for each study.

Figure 1. Research framework



Data Collection. For both studies questionnaires were distributed to US residents through Amazon Mechanical Turk (MTurk). To obtain quality data an approval rating (measure of respondent quality) of 99% or higher was required. While studies suggest that MTurk respondents are more attentive than survey pool participants (Hauser and Schwarz 2016), attention check questions were added in both studies. Those who failed to answer these questions correctly (less than 10% of survey takers for both studies) were removed from the dataset.

Data Analysis. The analyses followed Anderson and Gerbing's (1988) two-step approach, starting with confirmatory factor analysis (CFA) to test the adequacy of the measurement model, followed by a structural equation model (SEM) to test adequacy of the structural model for hypotheses testing, using the MPlus program (Muthén and Muthén 1998-2015). The analyses used MLM, a maximum likelihood parameter estimate with standard errors and a mean-adjusted chi-square test statistic (Satorra-Bentler corrections), which is robust to non-normality. Several criteria were used to assess the validity, reliability, and goodness of fit for both measurement and structural models (Hair et al. 2010; Hu and Bentler 1999). Finally, multi-group analysis was performed for each study to identify group differences.

4 Study 1: On-Demand Self-Driving Transportation

4.1 Background and Purpose

Recent research suggests that shared automated vehicles could play a vital role in society by providing inexpensive and sustainable transportation systems (Krueger, Rashidi, and Rose 2016). The emergence of peer-to-peer sharing systems is considered influential in providing sustainable choice for residents and tourists alike (Gössling, 2016). Integrating autonomous vehicles into the ridesharing systems will further emphasize these benefits. In fact, on-demand autonomous transportation service started when Uber added self-driving cars to its fleet in 2016 (Mitchell & Lien, 2016). Then, Lyft announced a partnership with General Motors to roll out on-demand network of autonomous cars and envisioned that the majority of Lyft service will be autonomous within five years (Zimmer, 2016).

To assess the future of on-demand autonomous transportation service, the adoption rate of this novel service operation remains a critical issue. Recent studies suggest that despite the benefits, the general public continues to express concerns about autonomous technology, which led to resistance to driverless vehicles (Schoettle and Sivak, 2014; 2015). In the 2014 study by Pew Internet (Smith, 2014), about 48% internet users in the US indicated interest in self-driving vehicles. Meanwhile, a 2016 report from American Automobile Association (AAA) shows that 75% drivers in the US are afraid to ride in self-driving cars (Hsu, 2016). Schoettle and Sivak (2014, 2015) conducted a series of studies about self-driving vehicles with consumers in China, India, Japan, the US, the United Kingdom, and Australia. They identified that consumers demonstrated high levels of concern about driverless cars, even though they were interested in and expected the benefits of autonomous car. Finally, Bazilinskyy, Kyriakidis, and De Winter (2015) conducted three online surveys with 8,862 respondents from 112 countries. They found the public opinion to be split between people having positive and those having negative opinion about fully automated driving, both being substantial in numbers.

As in adoption of various self-service technologies that have been studied in the past (Meuter et al., 2000; Meuter et al., 2005), the use of self-driving cars involves a significant behavior change in which important behavioral patterns must be altered. Self-driving cars bring computerization to driving, which has been considered exclusively a human function for over a century (Fagnant & Kockelman 2015). The concerns towards self-driving cars are entrenched in anxiety over changes to the various aspects of life, such as fear of technology following its own course (Dietterich & Horvitz, 2015), hesitation to give up autonomy and control of the activity of driving to a machine (Glancy, 2012), and concerns over diminishing demand for professional (human) drivers (Ross, 2014).

The purpose of Study 1 is to examine consumers' general attitude towards technology (H3) and assess its influence on the likelihood of using on-demand self-driving cars (H5) while traveling. Research has shown that consumers develop attitudes toward new technologies that they have not tried before and may be reluctant to change (Curran & Meuter, 2007). A better understanding on the various dimensions of attitude toward autonomous technology is essential in order to explain acceptance or rejection toward this technological innovation (see Davis, 1989; Davis, Bagozzi, & Warshaw, 1989; for the roles of attitudes on adoption of technologies).

4.2 Methodology

Measurements. An online questionnaire was developed to gauge consumers' attitudes toward technology, trust in self-driving car, and intention to use it while traveling. Trusting beliefs were operationalized as a second-order variable consisting of three first-order variables: functionality, helpfulness, and reliability (McKnight et al. 2011). Verified constructs and measurement items from previous studies (Lankton et al. 2014; McKnight et al. 2011) were adapted to the specific case of self-driving cars. General attitudes toward technology were measured using the Computer Attitude Scale (CAS) (Nickell & Pinto, 1986). It has been suggested that language plays a role in eliciting perception of technology (Sanchez 2015). Therefore, in order to identify whether people would respond differently to self-driving cars if they are referred to using different terms, this study measures negative attitude to computers and compares it with that to robots. The questionnaire was designed to randomly assign respondents into two groups: the "computer group" who responded to the original 20 items in CAS scale and the "robot group" who responded to modified items where the word "computer" was replaced by "robot" to test for the effect of these different interpretations Then, in order to gauge trusting intention to adopt on-demand autonomous transportation service, a scenario of a ride-hailing service with self-driving cars were presented and respondents were asked to state the likelihood of using this service while traveling (Table S2). These constructs were presented in 5-point scale with strongly disagree (1) – strongly agree (5) anchored statements (Table S1). For manipulation check, respondents were asked to state their agreement to the statement that self-driving taxi is a computer or a robot, respective of their group. Only those who correctly identified the scenario on the page after it was introduced could proceed.

Collected Data. Data was collected in July 2016 and March 2017 whereby no repeat participation was allowed. These resulted in 268 and 357 responses for batches one and two, respectively (Table 1).

Table 1. Study 1: Respondent Characteristics

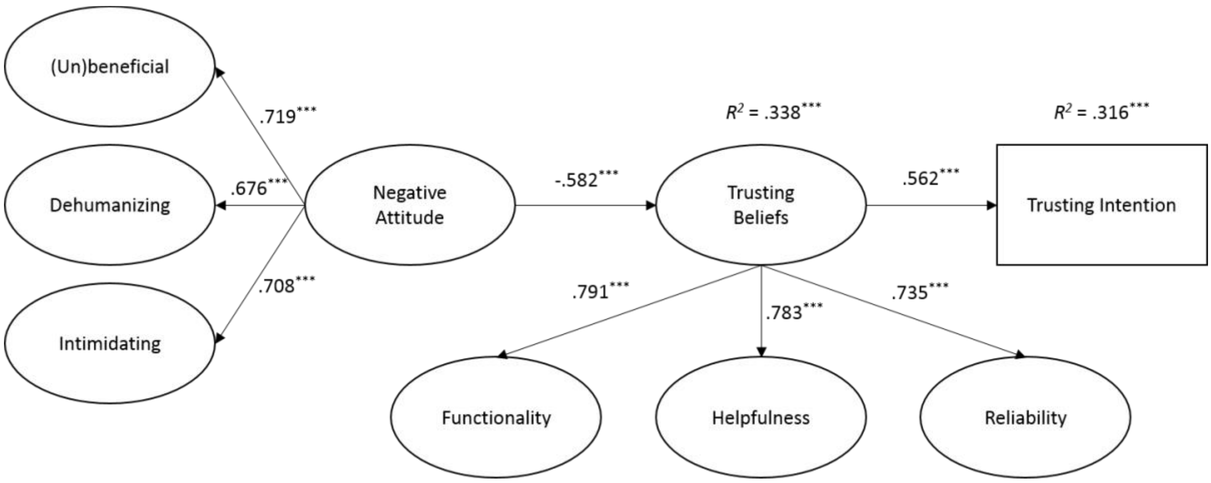
Characteristics	**Batch 1**	**Batch 2**	**Chi-Square (*p*-Value)**	**Computer**	**Robot**	**Chi-Square (*p*-Value)**
Gender			7.347 (.025)			.936 (.626)
Female	106	177		151	132	
Male	161	180		179	162	
Age			15.225 (.009)			3.649 (.601)
24 years and younger	36	21		36	21	
25 – 34 years	116	141		135	122	
35 – 44 years	59	95		76	78	
45 – 54 years	29	51		43	37	
55 – 64 years	22	33		28	27	
65 years and older	6	16		13	9	
Education			4.399 (.733)			5.409 (.610)
High School or less	34	40		32	42	
Some College	59	80		74	65	
2-Year College Degree	29	48		38	39	
4-Year College Degree	105	141		139	107	
Master's Degree	28	38		37	29	
Doctoral Degree	6	5		6	5	
Advanced Prof. Degree*	7	5		5	7	
Income (US$)			15.929 (.318)			15.729 (.330)
Under 20,000	43	42		49	36	
20,000 – 29,999	34	37		36	35	
30,000 – 39,999	41	40		41	40	
40,000 – 49,999	30	49		43	36	
50,000 – 59,999	24	35		25	34	
60,000 – 69,999	24	32		26	30	
70,000 – 79,999	21	30		25	26	
80,000 – 89,999	12	20		16	16	
90,000 – 99,999	18	23		21	20	
100,000 – 109,999	9	17		17	9	
110,000 – 119,999	2	9		7	4	
120,000 and above	8	22		22	8	

*Juris Doctor, Medical Doctor

4.3 Results and Discussion

The results demonstrate adequate convergent and discriminant validity of the measurement model (see supplementary materials). The structural model (Figure 2) shows significant paths from Negative Attitude to its lower-order variables: (Un)beneficial (β=.719, p<.001), Dehumanizing (β=.676, p<.001), and Intimidating (β=.708, p<.001). The paths from Trusting Beliefs to its lower-order variables are also significant: Functionality (β=.791, p<.001), Helpfulness (β=.783, p<.000) and Reliability (β=.735, p<.001). Negative Attitude has a significant negative effect on Trusting Beliefs (β=-.582; p<.001; R^2=.338; p<.001), providing support for H3. The significant positive effect of Trusting Beliefs on Trusting Intention (β=.562, p<.000; R^2=.316; p<.000) supports H5. It can be observed from the R^2 value that about 32% of the amount of variance in intention to use on-demand self-driving transportation when travelling can be explained by the model.

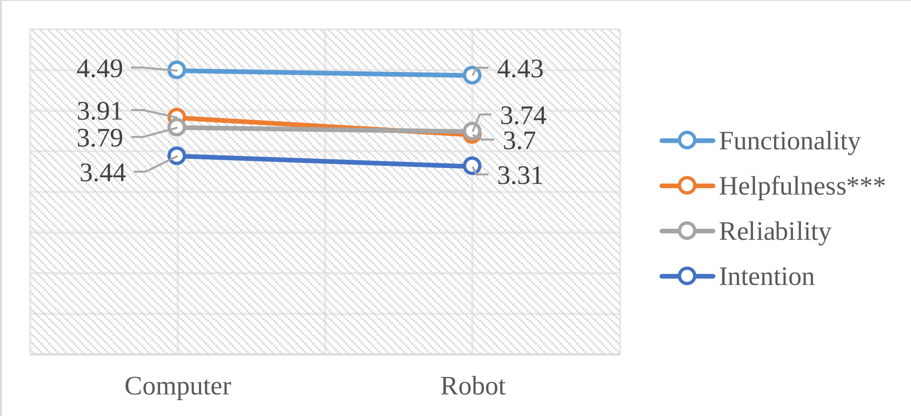
Figure 2. Study 1: The Structural Model



Note: Model Fit Criteria: AIC = 29653.800; BIC = 29964.242; Sample-size Adjusted BIC = 29742.002; Chi-square = 397.555; df = 182; p = .000; RMSEA = .044 (90%: .038 - .049); CFI = .968; TLI = .963; SRMR = .077; N = 625.

Based on the results, it can be suggested that developers need to communicate the benefits of autonomous transportation and to educate the public regarding how autonomous vehicles operate in order to eliminate the barrier to adoption of autonomous on demand mobility system. Communication about this service should emphasize that the use of autonomous vehicles would not lessen people's roles, but offer new types of employment instead. Further, a multi-group analysis was run between the computer and robot groups, but no significant differences were identified. A series of t-tests was run to investigate this further (Figure 3). The only significant difference was in perceived helpfulness (Computer: Mean=3.91, s.d.=.94; Robot: Mean=3.70, s.d.=1.01; t=2.699, p = .007), suggesting that language use in communicating new technology can influence consumers' perception of the technology, affecting adoption intention. Calling autonomous vehicles "robot cars" may cause consumers to perceive them as less helpful. Based on between-subjects effects tests, no influence of language use was identified on trusting intention (estimated marginal means of trusting intention: Robot=3.44; Computer=3.31; F=.328; p=.567).

Figure 3. Study 1: Mean Differences in Trusting Beliefs and Trusting Intention



Note: ** significant at p < .05.

5 Study 2: Robot Bartender

5.1 Background and Purpose

Research in service robotics has focused on the development of robots that can safely coexist, cooperate, and interact with humans in their daily environment, by facilitating human-friendly, natural human-robot interaction (Stiefelhagen et al. 2007). That is due to the nature of the tasks of service robots requiring them to deal with multiple customers in a multi-party social setting (Foster et al. 2012). In a simple bartending domain, studies have been conducted to develop technologies that enable natural multimodal interaction through state-of-the-art components for speech recognition, dialogue processing, computer vision, high level reasoning, and robot control (Foster et al. 2012; Giuliani et al. 2013; Keizer et al. 2013; Petrick & Foster 2013; Stiefelhagen et al. 2007). These technical elements are necessary to facilitate human-robot interactions that combine the task-based aspects and the social aspects of bartending. Although research has focused on developing humanoid robot bartenders, the commercial use of service robots for bartending is still limited to applications of automated robotic arm (e.g., Giuliani et al., 2013; Lukic, Billard, Santos-Victor, 2015), thus the approach to designing the robot is primarily on the task-based aspects of bartending.

In terms of consumer acceptance to robot bartenders, studies are dominated by user evaluation of developed robotic systems in laboratory settings, combining objective measures such as task completion with subjective measures of the human-robot interactions (Foster et al. 2012; Giuliani et al. 2013; Keizer et al. 2013; Petrick & Foster 2013; Stiefelhagen et al. 2007). For example, Foster et al. (2012) utilized a questionnaire to assess users' judgment of the robot bartender and the overall quality of the interactions. Similarly, Keizer et al. (2013) asked users to complete a short questionnaire regarding satisfaction with the interaction. While these studies are useful to understand the potential acceptance of the designed robot bartender, they do not provide a reliable ground to assess the potential success of commercially used robotic bar systems currently in the market. Therefore, a better understanding on how consumers view and respond to different service robots currently in operation, such as those adopted by cruise lines, will assist in better design and future application of service robots.

The purpose of Study 2 is thus to examine the effects of consumers' propensity to trust and general attitudes towards autonomous technology (H1 – faith in technology, H2 – trusting stance, H3 – negative attitude), as well as robot form on trusting beliefs in robot bartenders (H4) and, consequently, the effect of trusting beliefs on intention to use robot bartenders on board a cruise ship (H5). In order to examine the effect of robot form on trust, this study compares trust in robotic arm and in humanoid robots, while focusing on a particular interaction setting (a bar in a cruise ship).

5.2 Methodology

Measurement. Trusting beliefs were operationalized as in Study 1; verified constructs and measurement items were adapted to a specific case of robot bartenders. Faith and trusting stance in general technology were measured using the items tested in McKnight et al.'s (2011) study. To measure negative attitude toward robots, the original items from Negative Attitude towards Robots Scale (NARS) (Nomura et al. 2004; 2006a; 2006b) were used. The trusting intention is measured by two items measuring acceptance (Venkatesh and Davis, 1996). These constructs were presented in 5-point scale with strongly disagree (1) – strongly agree (5) anchored statements (Table S5). To assess the effect of robot form on trusting beliefs (H4), the questionnaire was designed to present two stimuli. Respondents were presented a scenario in which they were to plan a cruise trip and, through an extensive online search, found a cruise ship featuring a bar that is manned by robot bartenders. Then, they were randomly allocated to one of the two descriptions of a robot bartender: (a) robotic arm bartender or (b) humanoid robot bartender (using Pepper Robot). Thus, the study varies the service robot form (mechanical vs. humanoid), while keeping the same service context (bartending). Both robotic arm and humanoid robot bartenders such as Pepper have been developed and tested in research as well as applied in practice (e.g., Giuliani et al., 2013; Lukic et al., 2015), confirming realism of scenarios presented in this study. To control for respondents' familiarity with robotic bartenders, only those who have not used actual robot bartenders, in any forms, were included in the study (Table S6). As in Study 1 only those that correctly identified the scenario on the page after it was introduced could proceed.

Collected Data. In addition to the above mentioned MTurk quality measures respondents must have had an experience of taking a leisure cruise trip to exclude first-time cruise travelers and related first-time effects respondents. Data collection in June 2017 resulted in 533 responses: 258 responding to robotic arm scenario and 275 to humanoid (Table 2).

Table 2. Study 2: Respondent Characteristics

Characteristics	Total	Robot Arm	Humanoid	Chi-Square (*p*-Value)
Gender				2.755 (.097)
Female	278	125	153	
Male	255	133	122	
Age				7.516 (.185)
24 years and younger	59	33	26	
25 – 34 years	200	96	104	
35 – 44 years	130	57	73	
45 – 54 years	80	46	34	
55 – 64 years	46	17	29	
65 years and older	18	9	9	
Education				4.742 (.577)
High School	39	23	16	
Some College	124	59	65	
2-Year College Degree	65	36	29	
4-Year College Degree	212	96	116	
Master's Degree	73	37	36	
Doctoral Degree	7	3	4	
Advanced Prof. Degree*	11	4	7	
Income (US$)				9.993 (.763)
Under 30,000	106	55	51	
30,000 – 39,999	58	30	28	
40,000 – 49,999	56	27	29	
50,000 – 59,999	57	25	32	
60,000 – 69,999	60	32	28	
70,000 – 79,999	44	26	18	
80,000 – 89,999	30	15	15	
90,000 – 99,999	31	10	21	
100,000 – 109,999	27	12	15	
110,000 – 119,999	15	6	9	
120,000 and above	49	20	29	

*Juris Doctor, Medical Doctor

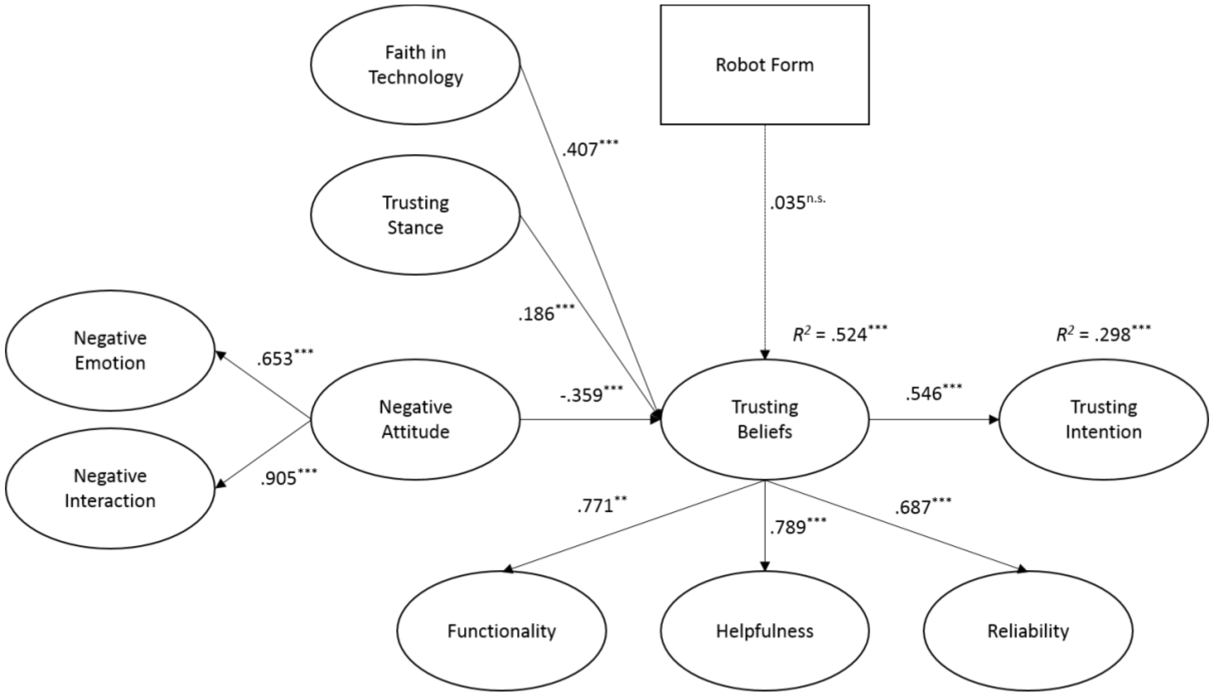
5.3 Results and Discussion

Several items in NARS did not load significantly to any constructs (with loadings below .4) and were thus dropped from the analysis. Indeed, while Nomura et al. (2004; 2006) argued that the NARS scale has been validated in multiple studies, others have suggested that the subcomponents might not apply to respondents outside Japan, where the original scale was developed (Syrdal et al. 2009). Hence, a final model with two sub-constructs of NARS, corresponding to negative attitude toward robots' emotion and interaction with robots, was identified. Adequate convergent and discriminant validity for the measurement model was found (see supplementary materials).

The trusting beliefs in robot bartender construct shows significant paths to its sub-constructs: functionality (β=.771, p<.001), helpfulness (β=.789, p<.001), and reliability (β=.663, p<.001). This confirms the applicability of trusting beliefs in service robots as a multidimensional variable consisting of expectations that robot bartenders possess the needed functionality to bartend, are able to provide users with effective help when needed, and will operate reliably and consistently without failing, in support of McKnight et al. (2011). The negative attitude toward robots have significant paths to its sub-constructs: negative emotion (β=.653, p<.001) and negative interaction (β=.905, p<.001). This suggests that consumers' predisposition to respond negatively to robots can be measured in terms of apprehension to the emotion of robots (i.e., people feel uneasy about the idea that robots have emotion) and the settings for interactions with robots (i.e., people are not comfortable interacting with robots).

The structural model is illustrated in Figure 4. Significant influences of faith in general technology, trusting stance, and negative attitude toward robots on trusting beliefs were identified. This confirms that higher faith in technology and higher trusting stance lead to higher trusting beliefs in service robots (McKnight et al. 2011). Lower negative attitude toward robots in general results in higher trusting beliefs toward robot bartenders, confirming previous research on NARS (Nomura et al. 2004; 2006). The results show no significant effect of robot form on trusting beliefs, indicating that consumers' trust in robotic arm bartenders, which is relatively high on average, is not significantly different from that in humanoid robots. Next, trusting intention is significantly influenced by trusting beliefs. This confirms that the cognitive trust formation process holds in the context of service robots, in support of previous trust research in technology artifacts (McKnight et al. 2011; Vance et al. 2008). Based on these results, Hypotheses 1, 2, 3, and 5 were supported, while Hypothesis 4 was rejected.

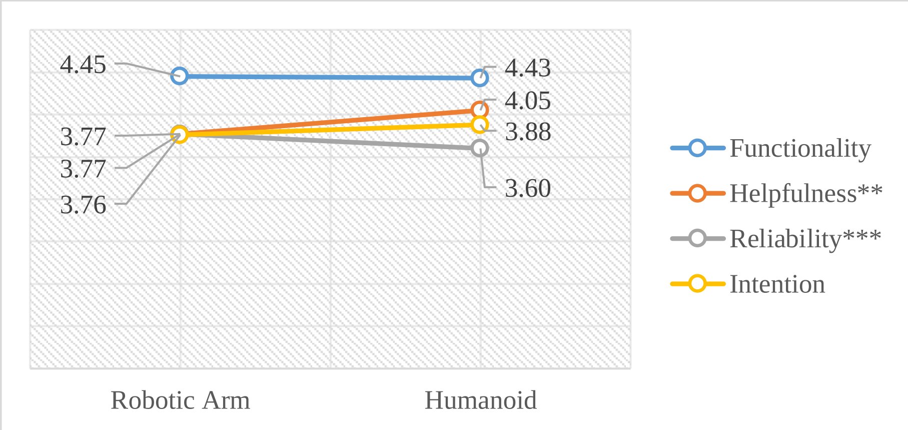
Figure 4. Study 2: The Structural Model



Note: Model Fit Criteria: AIC = 29653.800; BIC = 29964.242; Sample-size Adjusted BIC = 29742.002; Chi-square = 397.555; df = 182; p = .000; RMSEA = .044 (90%: .038 - .049); CFI = .968; TLI = .963; SRMR = .077; N = 625.

In order to explain the non-significant effect of robot form on trusting beliefs, independent-samples *t*-tests were performed on the aggregate means of the sub-constructs of trusting beliefs and trusting intention, comparing respondents to robotic arm and those to humanoid robot bartender (Figure 5). Significant differences were found in terms of helpfulness (Robotic arm: Mean=3.770, s.d.=.835; Humanoid: Mean=4.052, s.d.=.675; t=-4.300, p<.001) and Reliability (Robotic arm: Mean=3.770, s.d.=.916; Humanoid: Mean=3.599, s.d.=.946; t=2.121, p=.034). No significant difference was found in terms of functionality. This indicates that consumers have higher expectation that humanoid robot bartenders to be more helpful, but robotic arm bartenders to be more reliable. Further, between-subjects effects tests were also performed to estimate the influence of robot form on trusting intention. However, no significant effect was identified (estimated marginal means of trusting intention: Robotic arm=3.762; Humanoid=3.876; F=.981; p=.322). These results confirm that robot form does not yield different a rate of intention to adopt robot bartenders in the cruise ship context.

Figure 5. Study 2: Mean Differences in Trusting Beliefs and Trusting Intention



Note: *** significant at p < .01; ** significant at *p* < .05.

The results indicate that consumers with higher propensity to trust in general technologies expect intelligent robots, including robot bartenders, to be functional, helpful, and reliable. However, negative attitude toward robots in general is still a significant barrier to developing trust in intelligent robots among consumers. Further, this study only identified two sub-dimensions of negative attitude toward robots: emotion and interaction. The negative attitude toward social influence of robots, which demonstrates people's apprehension to robots casting influence on the society at large, was not identified. Syrdal et al. (2009) have suggested that the constructs within Negative Attitude to Robots Scale (NARS) may not be applied in different contexts, including in situations involving respondents with different cultural backgrounds. In contrast to previous studies utilizing android robots that triggered different reactions among consumers (e.g., Haring et al. 2013), the lack of applications of android robots in tourism and hospitality settings limited the scope of this study. That is, humanoid robots such as Pepper can still be considered less human-like even though they are designed to have some human characteristics in its appearance.

6. Conclusion and Implications

In order to better understand how travelers respond to the applications of intelligent service robots, this research explores trust formation based on two studies involving on-demand self-driving transportation and robotic bartenders. The results from both studies suggest that the cognitive trust formation process holds in the contexts where intelligent machines are the objects of trust. In both studies, trusting beliefs, measured as a multidimensional factor consisting of functionality, helpfulness, and reliability, had a significant positive effect on trusting intention, reflecting the likelihood to adopt/use service robots. This supports trust as key to the success of AI and robotic applications in tourism and hospitality settings, which is consistent with previous studies suggesting the importance of trust in consumer acceptance of autonomous technologies (McKnight, 2005; Tay et al., 2014; Wang and Benbasat, 2005; Yagoda and Gillan, 2012).

Several factors that contribute to and deter from trust were also identified. The negative attitude toward robots was found to significantly negatively influence trusting beliefs. In Study 1, negative attitude toward technology in general, measured with Computer Attitude Scale (CAS) (Nickell & Pinto, 1986), negatively affects trusting beliefs in self-driving vehicles. In Study 2, negative attitude toward robot in general, measured with Negative Attitude to Robots Scale (NARS) (Nomura et al. 2004; 2006a; 2006b), negatively influences trusting beliefs in robot bartenders. Specifically, consumers who perceive technologies as unbeneficial, dehumanizing, and complex, thus intimidating, will develop less trust toward specific autonomous technology such as self-driving vehicles. Likewise, consumers with negative attitude toward robots displaying emotion and toward interacting with robots will develop less trust toward service robots. These demonstrate how negative sentiment toward innovative technology in society can be a roadblock to adoption of intelligent robotic technologies.

Study 2 identified the positive influence of consumers' trusting propensity in general technology on trusting beliefs in robot bartenders. This is consistent to findings in previous studies on the significant roles of trusting propensity in influencing trust in technological systems in various contexts (e.g., Lee and Turban 2001; Wang and Benbasat 2005). Lastly, the influence of robot form on trusting beliefs was not identified, which inconsistent with findings from previous research regarding the roles of robot form in setting user expectation (e.g., Volante et al. 2016). Upon further investigation, it was found that consumers' trust in robotic arms and humanoid robots as bartenders differs in terms of helpfulness and reliability, with humanoid robots expected to be more helpful and robotic arms expected to be more reliable. Therefore, it can be suggested that in contexts where robots can take more assistive roles, or where consumers expect a higher degree of aids, humanoid robots can induce a higher level of trust compared to industrial-like robotic arms. Further, robot form does not have any effects on trusting intention, suggesting that adopting innovative service robots, regardless of the form, offers value in inducing adoption behavior. While the form of self-driving vehicles in Study 1 was not varied, respondents were randomly assigned to varying terms describing the vehicles: computer and robot. In terms of trusting beliefs, the only significant difference was found in terms of helpfulness, with those who were prompted that self-driving vehicle is a computer perceive a higher degree of helpfulness compared to those prompted that the vehicle is a robot. No significant difference in terms of trusting intention was identified. This implies the importance of carefully labelling new technologies, including branding, when introducing them to the market.

Theoretically, this research offers several contributions. First and foremost, it contributes to the validation of cognitive trust formation amongst consumers where intelligent service robots serve as objects of trust. As AI and robotics are increasingly integrated into tourism and hospitality encounters, explicating the relationships between trusting beliefs and their antecedents and outcomes is valuable to develop the knowledgebase on human-robot interactions in tourism service settings. Furthermore, by testing the model in different experience contexts (transportation and hospitality) using different intelligent machines (self-driving vehicles and robot bartenders), this research demonstrates reliability, as it supports replicability of research process and consistency in research findings. To support this further, future research applying the model to different settings and types of autonomous technologies is encouraged. Second, this research elucidates the relationship between global attitude towards technology and trust in specific technology (global to local, or generic to specific, concepts), by testing the effect of negative attitude towards technology/robots on trusting beliefs in self-driving vehicles and robot bartenders. Considering AI and robotics are highly debated in popular media (Fast and Horvitz, 2017), this research aids in how negative sentiments around AI and robotics that permeates society will cast a negative influence on acceptance of technological innovation in tourism, hospitality, and other sectors. Third, while the hypothesis was not supported, this research assists in clarifying the roles of robot form in trust formation, demonstrating that humanoid robots are considered more helpful than mechanical ones. This calls for further research to explore how consumers respond to a wider range of robot forms designed for the same operations, including human-like android robots. Finally, this research reveals how language used in communication regarding technologies can play a role in shaping consumer perception and, consequently, acceptance of its applications in travel, tourism and hospitality sectors. This opens an avenue for further research in this specific area. Experiments involving different terms and labels to communicate technological innovation to consumers and assessing their impacts on consumer trust and acceptance will provide useful insights into this issue.

Despite its contribution, this research has several limitations. First, different scales were used to measure negative attitude toward general technology/robot in the two studies: CAS and NARS. This was necessary due to the (lack of) relevance of measurement items with the study contexts. Both scales did not yield the same dimensions as suggested in the original studies, an outcome not unique to this research (Syrdal et al. 2009). This suggests a call for further studies to develop a scale to comprehensively measure general attitude toward service robots that accurately reflects and measures attitude of today's consumers. Second, the different research contexts represent different types and extent of risk of service failures: robot bartender mixing a wrong drink vs. self-driving vehicle involved in a traffic accident that may lead to fatality. On the one hand, this can be considered the strength of this research, as the consistency of the results demonstrates generalizability of the model along a wide spectrum of risk perception. On the other hand, there is a need to consider how risk perception directly influences trust formation. Therefore, it is suggested to include risk in trust formation model in future research. Third, this research targeted travelers who reside in the US. To incorporate the potential influence of national culture and other sociotechnical environmental factors linked to specific countries, further studies should include consumers from different countries and/or cultural backgrounds.

The practical contribution of this research can be summarized as follow. For tourism and hospitality managers looking to implement intelligent service robots into their operations, this research provides a guideline about the important factors to pay attention to in order to gain trust from consumers. In essence, two areas should be considered important: design and communication of technologies. First, companies need to generate positive sentiments in communication regarding technology to shape society's opinion about the benefits of intelligent machines. This will assist in reducing people's negative attitude towards robotics and autonomous technologies in general, which is demonstrated to negatively influence trust in intelligent service robots. Furthermore, companies should carefully craft their marketing messages to avoid labelling technologies that would generate negative perception amongst audience, such as referring to self-driving vehicles as “robot cars.” Importantly, as intelligent service robots are attractive to consumers who have a higher propensity to trust technology in general, it is important to target technology-savvy audience when designing and communicating innovative technological applications. Finally, for both service robotics manufacturers and business managers, it is important to match the physical forms of service robots with their intended functions in order to improve their trustworthiness. Consumers expect humanoid robots to be more helpful than industrial robots.

References

Adams, B.D., Bruyn, L.E., Houde, S., Angelopoulos, P. (2003), “Trust in automated systems literature review”, DRDC Report No. CR-2003-096, Defense Research and Development, Toronto, Canada.

Agag, G.M., El-Masry, A.A. (2016), “Why do consumers trust online travel websites? Drivers and outcomes of consumer trust toward online travel websites”, *Journal of Travel Research*, *56*(3), 347-369.

Anderson, J.C., Gerbing, D.W. (1988), “Structural equation modeling in practice: A review and recommended two-step approach”, *Psychological Bulletin*, *103*(3), 411-423.

Bartneck, C., Suzuki, T., Kanda, T., Nomura, T. (2007), “The influence of people's culture and prior experiences with Aibo on their attitude towards robots”, *AI and Society – The Journal of Human-Centred Systems*, *21*(1-2), 217-230.

Bazilinskyy, P., Kyriakidis, M., De Winter, J.C.F. (2015). “An international crowdsourcing study into people’s statements on fully automated driving.” Proceedings of the 6th International Conference on Applied Human Factors and Ergonomics (AHFE). Las Vegas, NV.

Beldad, A., de Jong, M., Steehouder, M. (2010), “How shall I trust the faceless and the intangible? A literature review on the antecedents of online trust”, *Computers in Human Behavior*, *26*, 857-869.

Billings, D.R., Shaefer, K.E., Chen, J.Y.C., Hancock, P.A. (2012), “Human-robot interaction: Developing trust in robots”, in *Proceedings of the 7th Annual ACM/IEEE International Conference on Human-Robot Interaction*, ACM, Boston, 109-110.

Brosnan, M.J. (1998), *Technophobia: The Psychological Impact of Information Technology*, Routledge, London.

Castelfranchi, C., Falcone, R. (2001), “Principles of trust for MAS: Cognitive anatomy, social importance, and quantification”, in *Proceedings of the International Conference on Multi-Agent Systems (ICMAS’1998)*, Paris, 72-79.

Chang, S.E., Hsieh, Y.J., Chen, C.W., Liao, C.K., Wang, S.T. (2006), “Location-based services for tourism industry: An empirical study”, in Ma, J., Jin, H., Young, L.T., and Tsai, J.J.P. (Eds.), *Ubiquitous Intelligence and Computing*. Springer, Berlin, 1144-1153.

Chen, C. (2006), “Identifying significant factors influencing consumer trust in an online travel site”, *Information Technology & Tourism*, *8*(3-4), 197-214.

Curran, J.M., Meuter, M.L. (2007). “Encouraging existing customers to switch to self-service technologies: Put a little fun in their lives.” Journal of Marketing Theory and Practice, 15(4), 283-298.

Davis, F. (1989). “Perceived usefulness, perceived ease of use, and user acceptance of information technology.” *MIS Quarterly*, 13(3), 319–340. http://dx.doi.org/10.2307/249008

Davis, F.D., Bagozzi, R.P., Warshaw, P.R. (1989). “User acceptance of computer technology: a comparison of two theoretical models.” *Management Science*, 35, 982–1003. http://dx.doi.org/10.1287/mnsc.35.8.982

Dietterich, T.G., Horvitz, E.J. (2015), “Rise of concerns about AI: Reflections and directions”, *Communication of the ACM*, *58*(10), 38-40.

DiSalvo, C.F., Gemperle, F., Forlizzi, J., Kiesler, S. (2002), “All robots are not created equal: The design and perception of humanoid robot heads”, in *Proceedings of the 4th Conference on Designing Interactive Systems: Processes, Practices, Methods, and Techniques,* London, 321-326.

Fagnant, D.J., Kockelman, K. (2015). “Preparing a nation for autonomous vehicles: Opportunities, barriers, and policy recommendations for capitalizing on self-driven vehicles.” *Transportation Research Part A*, 77, 167-181.

Fishbein, M., Ajzen, I. (1975), *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research,* Addison-Wesley, Reading, MA.

Fong T.W., Nourbakhsh, I., Dautenhahn, K. (2002), “A survey of socially interactive robots: Concepts, design and applications”, Tech. Report CMU-RI-TR-02-29, Robotics Institute, Carnegie Mellon University.

Foster, M.E., Gaschler, A., Giuliani, M. (2013), “‘How Can I Help You:’ Comparing engagement classification strategies for a robot bartender”, in *Proceedings of the 15th ACM International Conference on Multimodal Interaction*, ACM, Sydney, 263-270.

Gaudiello, I., Zibetti, E., Lefort, S., Chetuani, M., Ivaldi, S. (2016), “Trust as indicator of robot functional and social acceptance. An experimental study on user conformation to iCub answers”, *Computers in Human Behavior*, *61*, 633-655.

Gefen, D. (2002), “Reflections on the dimensions of trust and trustworthiness among online consumers”, *ACM Special Interest Group on Management Information Systems*, *33*(3), 38-53.

Giuliani, M., Petrick, R.P.A., Foster, M.E., Gaschler, A., Isard, A., Pateraki, M., Sigalas, M. (2013), “Comparing Task-based and Socially Intelligent Behavior in a Robot Bartender”, in *Proceedings of the 15th ACM International Conference on Multimodal Interaction*, ACM, Sydney, 263-270

Glancy, D.J., (2012). Privacy in autonomous vehicles. *Santa Clara Law Review*, 52(4), 1171-1239.

Gössling, S. (2016). *The Psychology of the Car. Automobile Admiration, Attachment, and Addiction*. Amsterdam, Elsevier.

Hair, J., Black, W., Babin, B., Anderson, R. (2010), *Multivariate Data Analysis,* 7th edition, Upper Saddle River, NJ, Prentice-Hall.

Hancock, P.A., Billings, D.R., Oleson, K.E., Chen, J.Y.C., de Visser, E.J., Parasuraman, R. (2011), “A meta-analysis of factors influencing the development of human-robot trust”, *Human Factors*, *53*(5), 517-527.

Hancock, P.A., Billings, D.R., Schaeffer, K.E. (2011), “Can you trust your robot?”, *Ergonomics in Design*, 24-29.

Haring, K.S., Matsumoto, Y., Watanabe, K. (2013), “How do people perceive and trust a lifelike robot”, in Kim, H.K., S.-I. Ao, and M.A. Amouzegar (Eds.), *Transactions on Engineering Technologies*. Springer, The Netherlands, 485-497.

Hauser, D.J., Schwarz, N. (2016), “Attentive Turkers: MTurk participants perform better on online attention checks than do subject pool participants.” *Behavior Research Methods*, *48*(1), 400-407.

Hsu, J. (2016). 75% of U.S. Drivers Fear Self-Driving Cars, But It's an Easy Fear to Get Over. *IEEE Spectrum*. http://spectrum.ieee.org/cars-that-think/transportation/selfdriving/driverless-cars-inspire-both-fear-and-hope.

Hu, L., Bentler, P.M. (1999), “Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives”, *Structural Equation Modeling: A Multidisciplinary Journal*, *6*, 1-55.

Ivanov, S., Webster, C. & Garenko, A. (2018). “Young Russian adults' attitudes towards the potential use of robots in hotels.” Technology in Society (in press)

Jarvenpaa, S.L., Knoll, K., Leidner, D.E. (1998), “Is anybody out there? Antecedents of trust in global virtual teams”, *Journal of Management Information Systems*, *14*(4), 29-64.

Keizer, S., Kastoris, P., Foter, M.E., Deshmukh, A., Lemon, O. (2013). User evaluation of a multi-user social interaction model implemented on a Nao robot. Proceedings of the ICSR 2013 Workshop on Robots in Public Spaces.

Kikuchi, M., Watanabe, Y., Yamanishi, T. (1996), “Judgment accuracy of other’s trustworthiness and general trust: An experimental study”, *Japanese Journal of Experimental Social Psychology*, *37*, 23-36.

Kim, J., McLean, J.E., Moon, S. (1994), “A Cross-Cultural Validation Study of the Computer Attitude Scale,” paper presented at the Annual Meeting of the Mid-South Educational Research Association, Nashville, Tennessee.

Koller, M. (1988), "Risk as a determinant of trust", *Basic and Applied Social Psychology*, *9*(4), 265-276.

Komiak, S.Y.X., Benbasat, I. (2006), "The effects of personalization and familiarity on trust and adoption of recommendation agents", *MIS Quarterly*, *30*(4), 941-960.

Kumar, N., Scheer, L.K., Steenkamp, J.E.M. (1995), "The Effects of Supplier Fairness on Vulnerable Resellers", *Journal of Marketing Research*, *32*, 54-65.

Kuo, C.-M., Chen, L.-C., & Tseng, C.-Y. (2017). Investigating an innovative service with hospitality robots. *International Journal of Contemporary Hospitality Management*, 29(5), 1305-1321.

Krueger, R., Rashidi, T.H., Rose, J.M. (2016). "Preferences for shared autonomous vehicles." *Transportation Research Part C: Emerging Technologies*, 69, 343-355.

Lankton, N.K., McKnight, D.H., Thatcher, J.B. (2014), "Incorporating trust-in-technology into Expectation Disconfirmation Theory", *The Journal of Strategic Information Systems*, *23*(2), 128-145.

Lee, J.D., See, K.A. (2004), "Trust in automation: Designing for appropriate reliance", *Human Factors*, *46*(1), 50-80.

Lee, M.K.O., Turban, E. (2001), "A trust model for consumer internet shopping", *International Journal of Electronic Commerce*, *6*(1), 75-91.

Li, L., Peng, M., Jiang, N., Law, R. (2017), "An empirical study in the influence of economy hotel website quality on online booking intentions," *International Journal of Hospitality Management*, *63*, 1-10.

Luhmann, N. (1979), *Trust and Power*, John Wiley, Chichester.

Lukic, L., Billard, A., Santos-Victor, J. (2015). Motor-primed visual attention for humanoid robots. *IEEE Transaction son Autonomous Mental Development*, 7(2), 76-91.

Mayer, R.C., Davis, J.H., Schoorman, F.D. (1995), "An Integrative Model of Organizational Trust", *The Academy of Management Review*, *20*(3), 709-734.

McKnight, D.H. (2005), "Trust in information technology", in Davis, G.B. (Ed.), *The Blackwell Encyclopedia of Management: Management Information Systems*, Vol. 7, Blackwell, Malden, MA, 329-331.

McKnight, D.H., Carter, M., Thatcher, J.B., Clay, P.F. (2011), “Trust in a specific technology: An investigation of its components and measures”, *ACM Transactions on Management Information Systems*, *2*(2), 1-25.

McKnight, D.H., Chervany, N.L. (2001-2002), “What trust means in e-commerce customer relationship: An investigation of its components and measures”, *International Journal of Electronic Commerce*, *6*(2), 35-59.

McKnight, D.H., Choudhury, V., Kacmar, C. (2002), “Developing and Validating Trust Measures for e-Commerce: An Integrative Typology”, *Information Systems Research*, *13*(3), 334-359.

McKnight, D.H., Cummings, L.L., Chervany, N.L. (1998), “Initial trust formation in new organizational relationships”, *Academy of Management Review*, *23*(3), 473-490.

Merritt, S.M., Ilgen, D.R. (2008), “Not all trust is created equal: Dispositional and history-based trust in human-automation interactions”, *Human Factors*, *50*(2), 194-210.

Meuter, M. L., Bitner, M. J., Ostrom, A. L., Brown, S. W. (2005). “Choosing among alternative service delivery modes: An investigation of customer trial of self-service technologies.” *Journal of Marketing*, *69*(2), 61-83.

Meuter, M. L., Ostrom, A. L., Roundtree, R. I., Bitner, M. J. (2000). “Self-service technologies: understanding customer satisfaction with technology-based service encounters.” *Journal of Marketing*, 64(3), 50-64.

Mitchell, R., Lien, T. (2016). “Uber as about to start giving rides in self-driving cars.” *Los Angeles Times*.http://www.latimes.com/business/la-fi-uber-self-driving-cars-20160818-snap-story.htm

Morgan, R.M., Hunt, S. (1994), “The commitment-trust theory of relationship marketing”, *Journal of Marketing*, *58*(3), 20-38

Morosan, C., DeFranco, A. (2016), “It’s about time: Revisiting UTAUT2 to examine consumers’ intentions to use NFC mobile payments in hotels”, *International Journal of Hospitality Management*, *53*, 17 – 29.

Muir, B.M. (1994), “Trust in automation: 1. Theoretical issues in the study of trust and human intervention in automated systems,” *Ergonomics*, *37*, 1905-1922.

Muthén, L.K., Muthén, B.O. (1998-2015), *MPlus User's Guide*, Seventh Edition, Muthén and Muthén, Los Angeles, CA.

Murphy, J., Hofacker, C.F., Gretzel, U. (2017), "Robots in hospitality and tourism: A research agenda", *eReview of Tourism Research, ENTER 2017: Volume 8 Research Notes*, http://ertr.tamu.edu/content/issues/enter-2017-volume-8-research-notes/

Nickell, G.S., Pinto, J.N. (1986). "The computer attitude scale." *Computers in Human Behavior*, 2, 301-306.

Nomura, T., Kanda, T., Suzuki, T. (2006), "Experimental investigation into influence of negative attitudes toward robots on human–robot interaction", *AI and Society*, *20*(2), 138-150.

Nomura, T., Kanda, T., Suzuki, T., Kato, K. (2004), "Psychology in human-robot communication: an attempt through investigation of negative attitudes and anxiety toward robots", in *Proceedings of the 13th IEEE International Workshop on Robot and Human Interactive Communication (RO-MAN 2004)*, 35-40.

Nomura, T., Suzuki, T., Kanda, T., Kato, K. (2006), "Measurement of negative attitudes towards robots", *Interaction Studies*, *7*(3), 437-454.

O'Donovan, J., Smyth, B. (2005), *Trust in recommender systems*, San Diego, CA.

Okamura, A.M., Mataric, M.J., Christensen, H.I. (2010), "Medical and health-care robotics: Achievements and opportunities", *IEEE Robotics and Automation Magazine*, 26-37.

Palaigeorgiou, G., Siozos, P., Konstantakis, N., Despotakis, T. (2004) "Computer experience: a multidimensional approach and a study." Proceedings of the 4th Hellenic Conference on Informational & Communication Technologies in Education, pp. 23–34.

Pan, Y., Okada, H., Uchiyama, T., Suzuki, K. (2015), "On the Reaction to robot's speech in a hotel public space", *International Journal of Social Robotics*, *7*(5), 911-920.

Pavlou, P.A., Gefen, D. (2004), "Building effective online marketplaces with institution-based trust", *Information Systems Research*, *15*(1), 35-53.

Petrick, R.P.A., Foster, M.E. (2013). "Planning for social interaction in a robot bartender domain." Proceedings of the 23rd International Conference on Automated Planning and Scheduling (ICAPS 2013), June 10-14, 2013, Rome, Italy.

Rosen, L.D., Weil, M.M. (1990), “Computers, classroom instruction, and the computerphobic university student”, *Collegiate Microcomputer, 8*(4), 275-283.

Ross, P.E. (2014). “How many lives will robocar technologies save?” *IEEE Spectrum*. http://spectrum.ieee.org/cars-that-think/transportation/advanced-cars/how-many-lives-will-robocar-technologies-save

Rotter, J.B. (1967), “A new scale for the measurement of interpersonal trust”, *Journal of Personality, 35*(4), 651-665.

Royal Caribbean (2016, September), “Robot Bartenders Shake Things Up at Sea.” http://www.royalcaribbean.com/connect/robot-bartenders-shake-things-up-at-sea/

Salam, A.F., Iyer, L., Palvia, P., Singh, R. (2005), “Trust in e-commerce”, *Communications of the ACM, 48* (2), 72-77.

Sanchez, D. (2015). “Collective technologies: autonomous vehicles.” Working Paper. Australian Council of Learned Academies. http://www.acola.org.au/PDF/SAF05/2Collective%20technologies.pdf

Schaefer, K.E., Sanders, T.L., Yordon, R.E., Billings, D.R., Hancock, P.A. (2012). “Classification of robot form: Factors predicting perceived trustworthiness”, in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 56*(1), 1548-1552.

Schoettle, B., Sivak, M. (2014). “Public opinion about self-driving vehicles in China, India, Japan, the US, the UK, and Australia.” Report No. UMTRI-2014-30. The University of Michigan Transportation Research Institute. Ann Arbor, MA.

Schoettle, B., Sivak, M. (2015). “Motorists' preferences for different levels of vehicle automation.” Report No. UMTRI-2015-22. The University of Michigan Transportation Research Institute. Ann Arbor, MA.

Smith, A. (2014). “U.S. views of technology and the future.” *Pew Internet*. http://www.pewinternet.org/2014/04/17/us-views-of-technology-and-the-future/

SoftBank Robotics (n.d.), “Costa Group is the First Cruise Company to Start Trialing Humanoid Robots.” https://www.ald.softbankrobotics.com/en/press/press-releases/pepper-costa

Stiefelhagen, R., Ekenel, H.K., Fugen, C., Gieselmann, P., Holzapfel, H., Kraft, G.F., Nickel, K., Voit, M., Waibel, A. (2007). Enabling multimodal human-robot interaction for the Karlsruhe humanoid robot. IEEE Transactions on Robotics, 23(5), 840-851.

Syrdal, D.S., Dautenhahn, K., Koay, K.L., Walters, M.L. (2009), "The negative attitudes towards robots scale and reactions to robot behavior in a live human-robot interaction study", in *Proceedings of the 23rd Convention of the Society for the Study of Artificial Intelligence and Simulation of Behavior*, 109-115.

Tay, B., Jung, Y., Park, T. (2014), "When stereotypes meet robots: The double-edge sword of robot gender and personality in human–robot interaction", *Computers in Human Behavior*, *38*, 75–84.

Thatcher, J.B., McKnight, D.H., Baker, E.W., Arsal, R.E. (2011), "The role of trust in postadoption exploration: An empirical investigation of knowledge management systems", *IEEE Transactions on Engineering Management*, *58*(1), 56-70.

Thrun, S. (2004), "Toward a framework for human-robot interaction," *Human–Computer Interaction*, *19*(1), 9-24.

Tung, V. W. S., & Law, R. (2017). "The potential for tourism and hospitality experience research in human-robot interactions." *International Journal of Contemporary Hospitality Management*, 29(10), 2498-2513.

Tussyadiah, I.P., & Park, S. (2018) Consumer Evaluation of Hotel Service Robots. *In*: Stangl B., Pesonen, J. (eds) Information and Communication Technologies in Tourism 2018. Springer, Cham, pp. 308-320.

van den Brule, R., Dotsch, R., Bijlstra, G., Wigboldus, D.H.J., Haselager, P. (2014), "Do robot performance and behavioral style affect human trust? A multi-method approach", *International Journal of Social Robotics*, *6*, 519-531.

Vance, A., Elie-Dit-Cosaque, C., Straub, D. (2008), "Examining trust in information technology artifacts: The effects of system quality and culture", *Journal of Management Information Systems*, *24*(4), 73-100.

Volante, W.G., Sanders, T., Dodge, D., Yerdon, V.A., Hancock, P.A. (2016), "Specifying influences that mediate trust in human-robot interaction," in *Proceedings of the Human Factors and Ergonomic Society Annual Meeting*.

Walker, G.H., Stanton, N.A., Young, M.S. (2001). Where is computing driving cars? *International Journal of Human-Computer Interaction*, *13*(2), 203-229.

Wang, L., Law, R., Hung, K., Guillet, B.D. (2014), "Scale development of perceived eTrust in the hotel industry: The perspective of internet users", *International Journal of Hospitality Management, 43,* 35 – 46.

Wang, L., Law, R., Guillet, C.D., Hung, K., Fong, C.K.C. (2015), "Impact of hotel website quality on online booking intentions: eTrust as a mediator", *International Journal of Hospitality Management, 47,* 108 – 115.

Wang, W., Benbasat, I. (2005), "Trust in and adoption of online recommendation agents", *Journal of the Association for Information Systems*, *6*(3), 72-101.

Wolbring, G., Yumakulov, S. (2014), "Social robots: Views of staff of a disability service organization", *International Journal of Social Robotics*, *63*, 457-468.

Yagoda, R.E., Gillan, D.J. (2012), "You Want Me to Trust a ROBOT? The Development of a Human-Robot Interaction Trust Scale. *International Journal of Social Robot*, *4*, 235-248.

Zimmer, J. (2016). "The third transportation revolution. Lyft's vision for the next ten years and beyond." *Medium*. https://medium.com/@johnzimmer/the-third-transportation-revolution-27860f05fa91

Statement of Contribution

1. What is the contribution to knowledge, theory, policy or practice offered by the paper?

   This research extends our knowledge of trust as a critical factor for intended applications of robotic technologies in a travel context. As such, it contributes to the validation of cognitive trust formation amongst consumers where intelligent service robots serve as objects of trust. As artificial intelligence and robotics are increasingly integrated into tourism and hospitality encounters, explicating the relationships between trusting beliefs and their antecedents and outcomes is valuable to develop the knowledge base on human-robot interactions in tourism service settings. The research model was tested in different experience contexts (transportation and hospitality) using different intelligent machines (self-driving vehicles and robot bartenders). It demonstrates reliability, as it supports replicability of research process and consistency in research findings.

2. How does the paper offer a social science perspective/approach?

   Our work provides a social science perspective as it contributes to the discourse of the use of technologies for travel experiences. This research studies travelers' behavior in the interaction with robotic technologies and elucidates the relationship between global attitude towards technology and trust in specific technology (global to local, or generic to specific, concepts), by testing the effect of negative attitude towards technology/robots on trusting beliefs in self-driving vehicles and robot bartenders. Considering artificial intelligence and robotics are highly debated in popular media, this research aids in how negative sentiments around AI and robotics that permeates society will cast a negative influence on acceptance of technological innovation in tourism, hospitality, and other sectors.

Supplemental materials

Study 1: On-Demand Self-Driving Transportation

A. Constructs and Measurements

Table S1. Constructs and Measurements

Constructs and Definition	Measurement Items	Literature
Computer Attitude Scale Positive and negative attitudes toward technology in society: computers (original) or robots (adaptation).	CAS1 – Computers will never replace human life.* (U) CAS2 – Computers make me uncomfortable because I don't understand them. CAS3 – People are becoming slaves to computers. CAS4 – Computers are responsible for many of the good things we enjoy.* (U) CAS5 – Soon our lives will be controlled by computers. (U) CAS6 – I feel intimidated by computers. CAS7 – There are unlimited possibilities of computer applications that haven't even been thought of yet.* (U) CAS8 – The overuse of computers may be harmful and damaging to humans. CAS9 – Computers are dehumanizing the society. CAS10 – Computers can eliminate a lot of tedious work for people.* (U) CAS11 – The use of computers is enhancing our standard of living.* CAS12 – Computers turn people into just another number. CAS13 – Computers are lessening the importance of too many jobs now done by humans. (U) CAS14 – Computers are a fast and efficient means of gaining information.* (U) CAS15 – Computers intimidate me because they seem so complex. CAS16 – Computers will replace the need for working human beings. (U) CAS17 – Computers are bringing us into a bright new era.* CAS18 – Soon our world will be completely run by computers. (U) CAS19 – Life will be easier and faster with computers.* CAS20 – Computers are difficult to understand and frustrating to work with.	Nickell & Pinto, 1986
Trusting Beliefs Nature of the Trustor's expectations regarding service robots.		Lankton et al. 2014; McKnight et al. 2011
Functionality Self-driving taxis demonstrate possession of the needed functionality to do the required task.	TBF1 – I expect that self-driving taxis will have the functionalities to serve me. TBF2 – I expect that self-driving taxis will have the features required to serve me. TBF3 – I expect that self-driving taxis will have the overall capabilities to serve me.	

Constructs and Definition	Measurement Items	Literature
Helpfulness Self-driving taxis are able to provide effective help when needed.	TBH1 – I expect that self-driving taxis will provide me with the help I need. TBH2 – I expect that self-driving taxis will provide competent guidance during service. TBH3 – I expect that self-driving taxis will supply my need for help through a help feature.	
Reliability Self-driving taxis operate reliably or consistently without failing.	TBR1 – I expect that self-driving taxis will not fail me. TBR2 – I expect that self-driving taxis will not malfunction on me. TBR3 – I expect that self-driving taxis will provide error-free service.	
Trusting Intention The extent to which a consumer is willing to depend on self-driving taxis.	TI1 – How likely are you to use self-driving taxis when travelling?	

Note: *Reversed scale; (U) Unidentified

B. Stimuli

Table S2. Definition and Stimuli

Definition: Computer	Definition: Robot
Computer *is a programmable electronic device designed to accept data, perform prescribed mathematical and logical operations at high speed, and display the results of these operations.*	***Robot*** *is any machine or mechanical device that operates automatically and does mechanical, routine tasks on command.*

Stimuli
Currently, a smart transportation system in which people get around in ***self-driving taxis*** *is being tested in several cities across the globe. It is expected that in the near future we will be able to hail* ***a self-driving taxi*** *with a quick touch on our smartphone screen. Self-driving taxis are equipped with* ***intelligent autonomous driving technology*** *that allows them to recognize traffic patterns in real time and navigate city streets more efficiently.*

Confirmation: Computer	Confirmation: Robot
"A self-driving taxi is a computer."	***"A self-driving taxi is a robot."***

C. Adequacy of Measurement Models

All factor loadings are above .6 and the average variance extracted (AVE) values of all latent variables are above the cutoff point of .5 (Hair et al. 2010), supporting convergent validity. The composite reliability (CR) values of all latent variables are above the cutoff criteria of .7 (Hair et al. 2010). The values of square roots of AVE of all latent variables are larger than the cross-correlations between the corresponding variable and any other variables, supporting discriminant validity. Further, the fit indices for the measurement model are above the thresholds of .9 (Hu & Bentler 1999): Comparative Fit Index

(CFI) = .968 and Tucker Lewis Index (TLI) = .963. The value of Root Mean Square Error of Approximation (RMSEA = .044) indicates good model fit and the value of Standardized Root Mean Square Residual (SRMR = .055) is below the threshold of .09 (Hu & Bentler 1999) (see Tables S1 and S2).

Table S3. Study 1: Factor Loadings, Composite Reliability (CR), and Average Variance Extracted (AVE)

	Factor Loadings	Composite Reliability	Average Variance Extracted
(Un)beneficial		.795	.564
UB → CAS11	.784		
UB → CAS17	.704		
UB → CAS19	.762		
Dehumanizing		.827	.547
DH → CAS12	.720		
DH → CAS3	.703		
DH → CAS8	.695		
DH → CAS9	.831		
Intimidating		.893	.677
INT → CAS15	.887		
INT → CAS2	.815		
INT → CAS20	.784		
INT → CAS6	.802		
Functionality		.941	.842
TBF → TBF1	.917		
TBF → TBF2	.903		
TBF → TBF3	.932		
Helpfulness		.882	.713
TBH → TBH1	.861		
TBH → TBH2	.840		
TBH → TBH3	.832		
Reliability		.960	.888
TBR → TBR1	.932		
TBR → TBR2	.958		
TBR → TBR3	.937		

Table S4. Study 1: Correlations and Square Roots of AVE

	Correlation					
	(1)	(2)	(3)	(4)	(5)	(6)
(1) (Un)beneficial	**.751**					
(2) Dehumanizing	.486	**.740**				
(3) Intimidating	.509	.478	**.823**			
(4) Functionality	-.331	-.311	-.326	**.918**		
(5) Helpfulness	-.328	-.308	-.322	.620	**.844**	
(6) Reliability	-.307	-.289	-.302	.581	.576	**.942**

Note: Square roots of AVE in the diagonal; AVE = average variance extracted; N = 625

Study 2: Robot Bartender

A. Constructs and Measurements

Table S5. Constructs and Measurements

Constructs and Definition	Measurement Items	Literature
Faith in General Technology One assumes technologies are usually consistent, reliable, functional, and provide the help needed.	FT1 – I believe that most technologies are effective at what they are designed to. FT2 – Most technologies have the features needed for their domain. FT3 – I think most technologies enable me to do what I need to do.	McKnight et al. 2011
Trusting Stance – General Technology Regardless of what one assumes about technology generally, one presumes that one will achieve better outcomes by assuming the technology can be relied upon.	TS1 - My typical approach is to trust new technologies until they prove me that I shouldn't. TS2 – I usually trust a technology until it gives me a reason not to trust it. TS3 – I generally give a technology the benefit of the doubt when I first use it.	McKnight et al. 2011
Negative Attitude toward Robots A relatively stable and enduring predisposition to react negatively to robots in general. A psychological or mental state that prevents humans to interact with robots.	NA1 – I would feel uneasy if robots really had emotions. NA2 – Something bad might happen if robots developed into living beings. NA3 – I would feel relaxed talking with robots. NA4 – I would feel uneasy if I was given a job where I had to use robots. NA5 – If robots had emotions, I would be able to make friends with them* NA6 – I feel comforted being with robots that have emotions* NA7 – The word ''robot'' means nothing to me. (U) NA8 – I would feel nervous operating a robot in front of other people. NA9 – I would hate the idea that robots or artificial intelligences were making judgments about things. (U) NA10 – I would feel very nervous just standing in front of a robot. NA11 – I feel that if I depend on robots too much, something bad might happen. (U) NA12 – I would feel paranoid talking with a robot. NA13 – I am concerned that robots would be a bad influence on children. (U) NA14 – I feel that in the future society will be dominated by robots. (U)	Nomura et al. 2004; 2006a; 2006b
Trusting Beliefs Nature of the Trustor's expectations regarding service robots.		Lankton et al. 2014; McKnight et al. 2011
Functionality Service robots demonstrate possession of the needed functionality to do the required task.	TBF1 – I expect that robot bartenders will have the functionalities to serve me. TBF2 – I expect that robot bartenders will have the features required to serve me. TBF3 – I expect that robot bartenders will have the overall capabilities to serve me.	
Helpfulness	TBH1 – I expect that robot bartenders will provide me with the help I need.	

Constructs and Definition	Measurement Items	Literature
Service robots are able to provide effective help when needed.	TBH2 – I expect that robot bartenders will provide competent guidance during service. TBH3 – I expect that robot bartenders will supply my need for help through a help feature.	
Reliability Service robots operate reliably or consistently without failing.	TBR1 – I expect that robot bartenders will not fail me. TBR2 – I expect that robot bartenders will not malfunction on me. TBR3 – I expect that robot bartenders will provide error-free service.	
Trusting Intention The extent to which a consumer is willing to depend on service robots.	TI1 – Given that I have access to robot bartenders, I intend to use it. TI2 – Given that I have access to robot bartenders, I predict that I would use it.	Venkatesh and Davis 1996

Note: *Reversed scale; (U) Unidentified

B. Scenarios

Table S6. Scenarios and Descriptions of Robot Form

Scenario	
You are planning to take a leisure cruise trip for seven (7) nights in the Caribbean departing from and returning to Miami, Florida. You did an extensive online search and found a new ship that features a bar with robot bartenders in addition to the features and attributes offered by other ships of the same star rating.	
Description: Robotic Arm Bartender	Description: Humanoid Robot Bartender
	
The bar is equipped with robotic arms that are mounted on the bar in place of bartenders. The robotic arms take orders directly from passengers via tablets located around the bar.	*The bar is equipped with humanoid service robots in place of bartenders. The robots take orders directly from passengers.*
The image was used with permission under CC-BY-NC-ND-2.0 License. Credit: Kat Jenkinson Link: https://www.flickr.com/photos/jenkinkn/25689423014/	The image was used with permission under CC.0 Public Domain License. Source: Pixabay

C. Adequacy of Measurement Models

All factor loadings are above .6; all latent variables have average variance extracted (AVE) values above the cutoff point of .5 (Hair et al. 2010), supporting convergent validity. The composite reliability (CR) values are above the cutoff criteria of .7 (Hair et al. 2010), indicating reliability. The values of square roots of AVE are higher than the cross-correlations between the corresponding variable and any other variables, supporting discriminant validity (see Tables 5 and 6). The model fit criteria for the measurement model are also supported, with χ^2/df less than 2.5 (χ^2 = 690.999, df = 312, p = .000) and fit indices above the thresholds of .900 (Hu and Bentler 1999): Comparative Fit Index (CFI) = .948 and Tucker Lewis Index (TLI) = .942. The value of the Root Mean Square Error of Approximation (RMSEA = .048) indicates good model fit (below .050; Hu and Bentler 1999) and the value of the Standardized Root Mean Square Residual (SRMR = .061) is below the threshold of .090 (Hu and Bentler 1999). Based on these criteria, it can be suggested that the measurement model is adequate (see Tables S7 and S8).

Table S7. Study 2: Factor Loadings, Composite Reliability (CR), and Average Variance Extracted (AVE)

	Factor Loadings	**Composite Reliability**	**Average Variance Extracted**
Faith in Technology		.758	.511
FAITH → FT1	.688		
FAITH → FT2	.705		
FAITH → FT3	.750		
Trusting Stance		.862	.677
STANCE → TS1	.850		
STANCE → TS2	.873		
STANCE → TS3	.739		
Negative Emotion		.866	.620
NEMO → NA1	.873		
NEMO → NA2	.781		
NEMO → NA5	.669		
NEMO → NA6	.812		
Negative Interaction		.850	.533
NINT → NA3	.685		
NINT → NA4	.789		
NINT → NA8	.629		
NINT → NA10	.728		
NINT → NA12	.809		
Functionality		.910	.771
TBF → TBF1	.856		
TBF → TBF2	.922		
TBF → TBF3	.854		
Helpfulness		.783	.548
TBH → TBH1	.786		

	Factor Loadings	Composite Reliability	Average Variance Extracted
TBH → TBH2	.766		
TBH → TBH3	.663		
Reliability		.915	.782
TBR → TBR1	.892		
TBR → TBR2	.880		
TBR → TBR3	.881		
Intention		.961	.925
INT → INT1	.991		
INT → INT2	.932		

Table S8. Study 2: Correlations and Square Roots of AVE

	Correlation							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
(1) Faith in Technology	**.715**							
(2) Trusting Stance	.440	**.823**						
(3) Negative Emotion	-.183	-.226	**.787**					
(4) Negative Interaction	-.253	-.312	.592	**.730**				
(5) Functionality	.457	.376	-.272	-.375	**.878**			
(6) Helpfulness	.464	.382	-.276	-.381	.607	**.740**		
(7) Reliability	.408	.336	-.242	-.335	.533	.542	**.884**	
(8) Trusting Intention	.322	.266	-.192	-.265	.422	.428	.376	**.962**

Note: Square roots of AVE in the diagonal; AVE = average variance extracted; N = 533