심리학 석사 학위논문

The Influencing Factors of Trust in Human-like Agents

사람과 인공지능 에이전트의 상호작용에서 신뢰에 영향을 미치는 요인들

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이 용 은

Abstract

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Various interactive intelligent agents have begun to appear in everyday lives, through smartphones and home appliances. In the present study, we used the Wizard of Oz methodology to explore potential factors that influence users' perception and trust of intelligent agents. We used a smart speaker as a representative of AI agents and investigated how personality traits of a user, voice pitch and interactive style of the agent affected perception and trust of AI agent. In study 1, we manipulated voice pitch of a smart speaker and users had a small talk with the speaker, asking it to do scheduling and making reservations, playing a word chain game, and asking for a weather forecast. In study 2, we used the same task as study 1, but manipulated the interaction style (active vs. passive) of the smart speaker. Higher voice pitch was perceived more positively than lower voice pitch, and higher voice pitch led to increased trust. The interaction style such that whether smart speaker initiated the conversation did not affect perception of AI agent or the trust. In terms of the personality trait of a user, the honesty-humility factor of HEXACO personality inventory influenced trust in the AI agent. The results revealed that human-like qualities (e.g.

having intelligence, being nice) positively impact trust in the AI agents and how users interact with them. The present study can be used to improve design of AI agents in daily life through understanding factors influencing trust in human-AI interaction.

Keywords: trust, human-robot interaction, artificial intelligence agents

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Table of Contents

List of Tables

List of Figures

Chapter 1. Introduction

1. Human-like Agents with Voice User Interface

Voice user interface (VUI) has become ubiquitous in everyday devices. Smartphones, speakers, and cars are equipped with software agents. Apple’s Siri, Microsoft’s Cortana, Google’s Assistant, and Amazon’s Alexa are voice assistants that execute minor tasks by taking verbal orders from the user. For example, when the user commands “Hey Siri, wake me up at 8 o’clock,” Siri will set an alarm for 8 AM on the user’s phone. Drawing on the user’s everyday language, spoken interaction is intuitive and efficient. Moreover, users can engage in different activities with their hands and eyes while interacting with VUI (Cohen, Giangola, & Balogh, 2004). This characteristic is particularly useful for those with disabilities. People with visual impairment or motor limitations find VUI especially helpful and satisfactory (Pradhan, Mehta, &Findlater, 2018). Older adults also find voice interface easier to use rather than other input devices such as keyboard and mouse (Looije, Neerincx, &Cnossen, 2010; Portet et al., 2013). The participants of the study by Portet and colleagues commented that VUI is a “great economy of movement and fatigue.”

The convenience of VUI has led to its implementation in smart speakers such as the Amazon Echo and Google Home to permeate into everyday life. Twenty-one percent of Americans own a smart speaker, equating to 118.5 million smart speakers across American households (NPR & Edison Research, 2019). Smart speakers not only function as virtual assistants, but also as hubs for smart home devices, such as smart lights and smart home security. As a hub, a smart speaker will manage lights in the home, control room temperature, and monitor visitors approaching the house. By sitting at a desk and commanding “turn off the TV,” users can turn off the TV without moving a finger. Forrester Analytics forecast that 134.8 million smart speakers will be installed in the United States in the next five years (Tiwari, Gillett, & Meena, 2019). In a study with Google Home, the median household issued 4.1 commands to their device daily. The most used command was music playback, followed by information, automation, and small talk (Bentley et al., 2018).

Figure 1 Connectable applications and services with smart speaker (KEIT, 2018)

2. Social Isolation and Conversational Agents

Conversational agents are expected fill the gap of social interaction deprivation. Many research literatures support that conversational agents with social intelligence are able to provide social support and assistance to people. Socially expressive conversational agents are perceived as more enjoyable and having bigger social presence than their inexpressive counterparts (Heerink et al., 2010). When embedded in a home environment, conversational agents with social intelligence promote comfort (De Ruyter et al., 2005). The growing aging population has inspired researchers to examine the effect of conversational agents in care homes. Paro, a seal shaped social robot increased vigor and promoted conversation in the elderly (Wada et al., 2002). When the effect of interaction with Paro was further examined as a long-term study, it was found that the interaction improves moods and depression, decreases stress level; this effect was prolonged up to one year in the older population (Wada et al., 2005). A social robot, AIBO, reduced loneliness in the elderly and improved emotional state (Tamura et al., 2004). In the case of children, social presence of the conversational agent promoted relationship building between the child and the agent, suggesting children are able to build a valid relationship with the agent (Short et al., 2014).

Conversational agents taking the role as a social support provider is achieved through relationship building. To be successful in taking the role, the agents should be perceived as “human-like,” capable of developing a personal relationship. Anthropomorphism, the tendency of people to rationalize the behavior of non-human beings by attributing human characteristics, such as voice, gender, and name, can facilitate human-agent interaction (Duffy, 2003). The more the agent seems to have human-like qualities, the more competent and trustworthy the agent is perceived to be (Epley, Caruso, & Bazerman, 2006; Nass & Moon, 2000). The elderly treats the conversational agents as if they were interacting with humans (Heerink et al., 2008). During a verbal interaction with a computer, participants were polite to the computer, suggesting that anthropomorphizing the computer led to the application of social rules and behaviors (Nass & Moon, 2000). Interestingly, people tend to anthropomorphize the agent with the same gender as themselves and felt psychologically closer than the agent with the opposite gender (Eyssel et al., 2012). Careful consideration for user characteristics and anthropomorphic features for conversational agent will aid in social interaction and relationship development for the users, especially those in need of social support.

3. Trust

Trust influences the intention to rely on automation (Lee & See, 2004). Appropriate level of trust guides the user to accept intelligent personal assistants (IPAs) and increase the reliance on the technology (Lee & Moray, 1994; Merritt &Ilgen, 2008; Wang, Jamieson, & Hollands, 2009). In addition, trust influences the user's willingness to accept the information produced by the IPA, adopt its suggestions, and consequently benefit from the technology (Hancock et al., 2011). Utilization of an IPA can reduce mental workload of the user and increase psychological closeness to the IPA (Parasuraman, 1997; Salem et al., 2015).

Smart speakers make online orders and handle private information. Therefore, security is a key concern for the users. These voice-controlled intelligent personal assistants (IPAs) constantly listen through embedded microphones for the activation keyword ("Alexa" or "Hey Siri"). Then, the user's verbal request is sent to the parent company's server to be processed before IPA responds to the request. This cloud-based processing poses a security threat to the user (Lau, Zimmerman, & Schaub, 2018). Users' privacy concerns ranged from fear of identity theft to sharing of data with third parties (Naeini et al., 2017). There is a risk of a third party making unauthorized online purchases or accessing personal information. Moreover, there is a potential that the user data may be stolen or leaked (Hoy, 2018). Thus, in addition to security related technical advancement by the manufacturing company, the user's trust for the system will affect the use and acceptance of IPAs.

In order for trust to be formed, social relationship should be present (Lewis &Weigert, 1985). A person with social intelligence has congeniality, social technique, ease in society, knowledge of social matters, and insight into the emotions and personality traits of others (Vernon, 1933). Like humans, IPAs can convey its social intelligence to the person with whom it is interacting. When compared with non-social agents, agents with social qualities are perceived as better personal assistants and are rated to be more intelligent (De Graaf &Allouch, 2013; Looije, Neerincx, &Cnossen, 2010). With more human-like social intelligence, users are more willing to trust the technology. They also regard sociability of the system to be more important than the system intelligence (Waytz, Heafner, & Epley, 2014; De Graaf &Allouch, 2013). Social intelligence embedded IPAs induce more positive attitude towards the technology (De Ruyter et al., 2005). In addition, socially expressive agents are rated to be more enjoyable and receive higher intention of use (De Graaf &Allouch, 2013; Heerink et al., 2010). One of the function of IPAs is small talk, which conveys social intelligence to the user. Small talk is a social language where interpersonal goal is emphasized rather than task goals. Through small talk, common ground is established, which leads to familiarity and solidarity. Consequently, trust level increases with increase in social interaction (Cassell&Bickmore, 2003). In case of personality traits, extroverts are more trusting of social IPAs that establishes a relationship with the user through small talk, while introverts find IPAs that focuses only on the task more credible (Cassell&Bickmore, 2003). Social aspect of IPAs effect trust differently by culture as well. Highly collectivist cultures, such as Chinese and Korean culture tend to have increased engagement in social interaction with IPAs and have higher trust in the agent compared to individualist cultures, like Germany (Li, Rau, & Li, 2010).

4. Characteristics of Speech

Precise speech recognition is important in interaction with users. Conversation is a central component of interaction for VUI (Webb et al., 2010). Social relationships are formed and maintained through conversation. Automatic Speech Recognition (ASR) are generally based on Hidden Markov Modal (HMM). The user's voice input containing the utterance and background noise is processed through signal processing algorithm by speech recognition engine. It then converts the audio input into text format. The recognition engine searches for the matching vocabulary and grammar to its knowledge then provide response through text-to-speech (TTS) synthesis system (Duarte et al., 2014; Kamble, 2016; Reynolds, 2002). Smart speakers are frequently utilized as hub for smart home environment and Internet of Things (IoT). Thus, consideration for all age groups and user characteristics is imperative for ASR so that it can find the best match for user's utterances in its knowledge environment. When given an appointment scheduling task, younger users were task-oriented, while older users attempted social interaction with IPA. Older users used dialogues that are more appropriate in interaction between humans, such as "good-bye" or "thank you." Moreover, they produced significantly more distinct word types and tokens than younger individuals. Therefore, the ASR trained on younger user data was unable to understand utterances by the older users (Vipperla et al., 2009). In case of children, speech recognition performance could be improved by more training data (Wilpon& Jacobsen, 1996). Cultural and individual differences thus should be considered for natural social interaction with IPAs that interact verbally to enhance trust and acceptance of the system.

Speech provides the listener with the information about the speaker. From years of research, it is well established that emotion, personality, background, and educational status is conveyed through speech (Apple, Streeter, & Krauss, 1979; Aronovitch, 1976; Harms, 1961; Sanford, 1942).

Extroversion can be inferred through vocal cues such as voice energy, and voice pitch, whereas introversion is associated with loudness and slower speech rate (Apple, Streeter, & Krauss, 1979; Scherer, 1978). Speech seems to override the aesthetic appeal of the speaker when evaluating intelligence. Attractive individuals are rated as more intelligent, until others can hear their speech. When the utterances are present, people rate intelligence based on verbal cues rather than the physical attractiveness (Borkenau&Liebler, 1993).

Similar to human-human interaction, vocal cues influence human-robot interaction. Social agency theory suggests that social cues, such as face and voice prime the user to interpret interaction with the robots as interaction with humans (Mayer, Sobko, &Mautone, 2003; Louwerse et al., 2005). Apple's voice assistant Siri users stated that its human-like voice made it more user friendly (Cowan et al., 2017). In case of older adults, natural (human) speech was evaluated as more pleasant, intelligent, interesting, soothing, and clear compared to synthetic speech. Among the natural speech, the male voice was rated more positively than the female voice when presenting technical information (Lines & Hone, 2006). Similarly, college students rated the computer with natural speech as more dynamic, attractive, and superior than the one with synthetic speech (Mayer, Sobko, &Mautone, 2003).

5. The Influence of Voice Pitch

Voice pitch has a great importance in how the speaker is perceived and what emotion and personality the speaker conveys to the listener. Higher mean pitch reflects active emotions such as anger and fear, while lower mean pitch expresses sorrow and indifference. Tsantani and colleagues found that low-pitched voice is judged to be more dominant and trustworthy in men (2016). In case of female voice, lower pitched voices were perceived to be more dominant and higher pitched voices were assessed as more attractive up to an optimal pitch of 280Hz (Borkowska&Pawlowki, 2010). In economic and mate poaching context, higher pitched female voices were more trusted, but lower pitched voices were more trust in general. The opposite result was observed for male voices, with more trust in low pitched voices and less trust in higher pitched voices (O’Connor & Barclay, 2017). Female voice pitch and attractiveness judgment are positively correlated, where higher pitch was perceived as more attractive (Collins & Missing, 2003; Apicella& Feinberg, 2009).

In human-robot interaction, the preference for gender and the pitch of voice of the robot is different depending on the context and the information the agent is providing. Eyssel and colleagues found that females prefer robots with female voice whereas males prefer robots with male voice

(2012). When the voice of the robot was only female, users preferred a higher-pitched voice to a lower-pitched voice. The robot with the higher-pitched voice was perceived to be more appealing and was rated as having a more appealing behavior and a more extroverted personality. Moreover, the robot was perceived to be more emotional than the robot with lower-pitched voice. However, the lower-pitched voice robot was perceived to be stronger more rational (Niculescu et al., 2013). When elders interacted with the smart home device through speech, half of the participants preferred the female voice to the male voice, one preferred the male voice, and the remaining participants stated that it did not matter (Portet et al., 2013). When participants received evaluation of a test they took, a female voice evaluator was perceived as significantly less friendly than the male-voice evaluator (Nass, Moon, & Green, 1997). The primary function and purpose of a robot affects the voice gender and voice pitch preferences. More research on individual and cultural differences is needed to understand the nuances.

6. Current Research

The current study explores the influencing factors of trust in human-like agents. We manipulated components of verbal interaction to investigate perception of the human-like agents and trust. Particularly, we used smart speakers as a representative for human-like agent. In study 1, we investigated how voice pitch, the most prominent characteristic of voice user interface, influences trust. We also explored how voice pitch influences user's perception of the agent and its effect on trust. We used Godspeed Questionnaire (Bartneck, Kulic, & Croft, 2008) to measure how much the participants anthropomorphized the smart speaker and how users perceived it. Human-Computer Trust scale (Madsen & Gregor, 2000) was used to measure user trust (e.g. The system always provides the advice I require to make my decision). In addition, we utilized trust game (Berg, Dickhaut, & McCabe, 1995) that measures how much the users trust the smart speaker will behave selflessly. In study 2, we manipulated interaction style of the AI agent, so that the smart speaker was either active or passive. The active smart speaker interacted with the user even when not prompted. The passive smart speaker responded only when it was spoken to. In addition, personality traits of the users were measured to explore the individual differences of the users and its influence on trust.

Chapter 2. Study 1

1. Hypotheses

Study 1 investigated how different pitches of voice of smart speaker influences perception of the smart speaker and trust. Empirical research has found that AI agents with higher voice pitch are perceived as more extroverted and appealing (Niculescu et al., 2013). Thus, we hypothesized that perception of the AI agent (anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety) would increase with increase in voice pitch. We also hypothesized that trust would increase with increase in voice pitch. We predicted that users will place more trust in AI agents that are rated more positively. To investigate this prediction, we hypothesized that the perception of the AI agent would mediate the effect of voice pitch on user trust.

2. Method

Participants. Participants were recruited online (Sona Systems, Ltd.). A total of 40 participants were recruited and 25 were female. All participants were undergraduate students (M_{age}= 20.48, SD = 2.49). They were provided with a written description of the experiment and a signed consent was obtained for each participant. Only those who do not own a smart speaker were recruited to avoid preference for familiar voice. The participants were randomly assigned to four different voice pitch conditions (*N* = 10 for each condition).

Measures and Design. There were four voice pitch conditions: high, medium, medium-low, low. The voices were all female voices and were generated using Text-to-Speech (TTS) engine from online sources (Naver Corp. &Oddcast). The frequency of high pitch condition was 237Hz, medium was 202Hz, medium-low was 188Hz and low condition pitch frequency was 183Hz. Participants were randomly assigned to each condition, interacting with only one voice pitch. The volume of the speaker used was tuned to an average of 50 dB.

To explore the influencing factors of voice pitch on user trust and perception of the AI agent, we used the following measures.

Perception of smart speaker. We used Godspeed questionnaire (Bartneck, Kulic, & Croft, 2008) to assess perception of smart speaker. The subscales of the questionnaire include anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety. The Korean translation of the questionnaire was obtained from the author’s website (http://www.bartneck.de/work/researchProjects/socialRobotics/godspeed). The items of the questionnaire consist of two opposite words on each end. The participant selects the score that is closer to the word that describes the smart speaker on a 5-point Likert scale. We excluded one item (moving rigidly vs. moving elegantly) since the smart speaker does not have any movement.

User Trust. We used Human Computer Trust scale (HCT; Madsen & Gregor, 2000) to measure user trust. The subscales of the questionnaire include perceived reliability, perceived technical competence, perceived understandability, faith, and personal attachment on a 5-point Likert scale.

Trust. We used Trust game (Berg, Dickhaut, & McCabe, 1995) which measures trust through a simple game involving money. Among ₩10,000, the participant chooses how much they would like to send to the smart speaker. They are told that the speaker receives three times the money they send to the speaker. Among the tripled money, the speaker makes an arbitrary decision on how much money they will send back to the participant. For example, if the participant selects ₩5,000, the smart speaker receives ₩15,000 and decides how much money it will give back to the participant. Therefore, the participant can lose or gain money, depending on the smart speaker's decision.

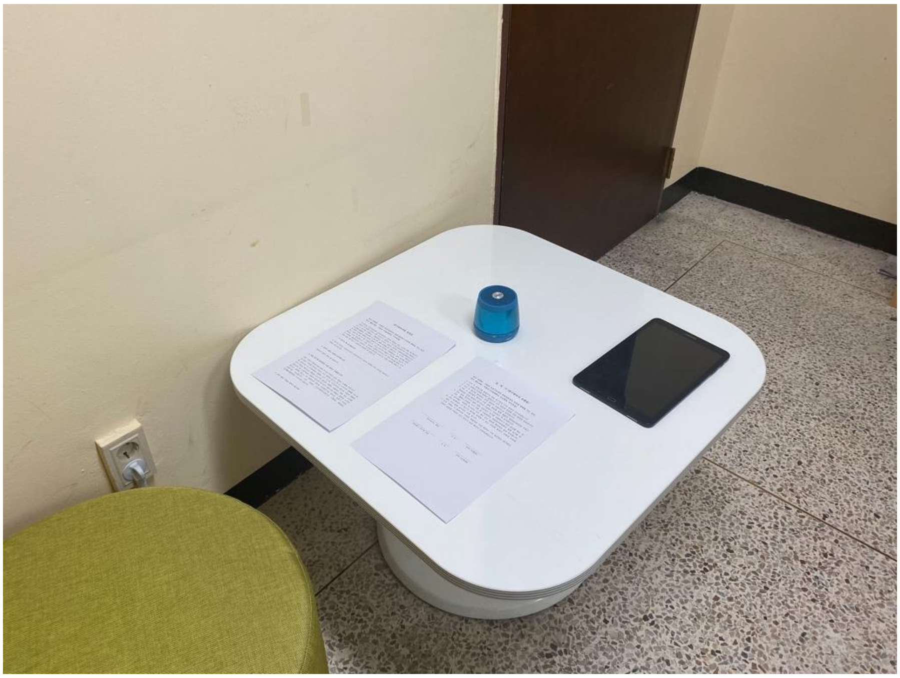

Figure 2 Experiment setting

Procedure. Upon arrival, participants were guided to a couch in front of a table. On the table, the smart speaker was located in the center. After they signed the consent form, they were given the study scenario:

> *You are here to pick up your friend and to go somewhere else to hang out. However, your friend has left the house for a brief moment. While your friend is out, you are going to interact with the smart speaker that your friend owns. The smart speaker will lead the conversation and all interaction will occur verbally.*

We used Wizard of Oz methodology (Bradley et al., 2009). The experimenter (the wizard) in a separate location where they cannot be seen listened to the participant and selected the appropriate response for the smart speaker to say from the script. The participants believed that they were interacting with an actual smart speaker and not a person. When the experimenter left to a separated location, the smart speaker initiated the conversation by introducing itself.

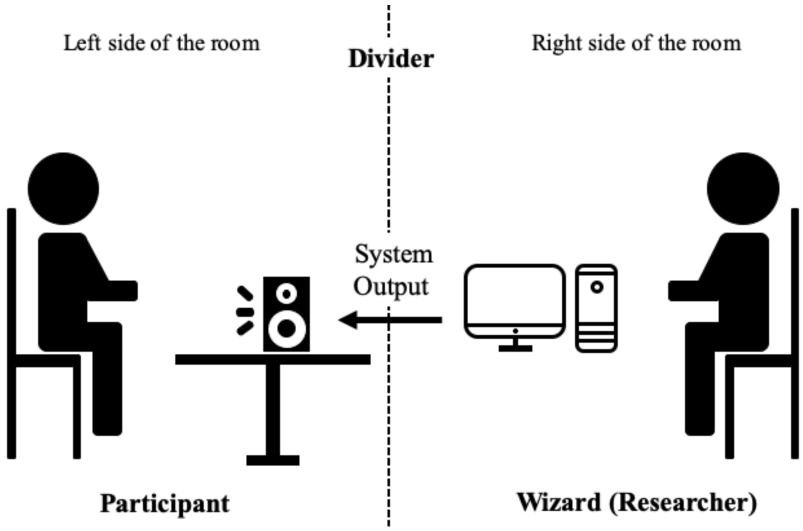

Figure 3 Wizard of Oz setup

There were four conversational topics: small talk, scheduling and recommendations, word chain game, and weather information. The conversation was designed to demonstrate social and assistive features of the smart speaker. Small talk consisted of questions people might ask when they are getting acquainted (name, favorite food, color, hobby, etc.). Scheduling and recommendations started with a question, “what are you planning to do today with your friend?” The smart speaker recommended and provided adequate information. For example, when the smart speaker recommended watching a movie, it told the participant what movies are currently showing at the movie theater. Then it reserved tickets for the movie if the participant wanted. Word chain game is a commonly played game, where two people take turns to say the word that starts with the syllable the previous word ended with. For example, if one person says “train”, the other person would say a word that starts with “in” sound, such as “indicator” or “intuition.” The smart speaker suggested playing this game while waiting for the participant’s friend. After the game went on for about 2 minutes, the smart speaker informed the participant that their friend has almost arrived. Then it provided the weather information and suggested wearing a mask (or not wearing) given the level of microdust.

After the conclusion of the conversation with the smart speaker, the experimenter came back and asked the participant to fill out a survey on the tablet. The survey consisted of HCT questionnaire and Godspeed questionnaire. When they finished the survey, the experimenter conducted a short interview on how they felt about the interaction. Then they were debriefed about the Wizard of Oz methodology and were thanked.

3. Results

Perception of the smart speaker. High pitch condition was most positively perceived, while low pitch condition was least positively perceived, supporting the hypothesis (Table 1). The mean score of the Godspeed questionnaire for high and low conditions were compared using two-tailed t-test. The Godspeed questionnaire scores were significantly different between high pitch and low pitch conditions ($t(18)=2.12$, $p<.05$, $d = 0.948$). One-way ANOVA was conducted to compare the means across the four conditions. The means were not significantly different among the groups ($F(3, 36) = 1.51$, p = n.s.). However, the graph reveals there is a decreasing pattern. Voice pitch condition and perception of the AI agent were marginally correlated ($r = -.298$, $p = 0.06$). For the correlation analysis, the voice pitch condition was coded as following: *high* = 1, *medium* = 2, *medium-low* = 3, *low* = 4.

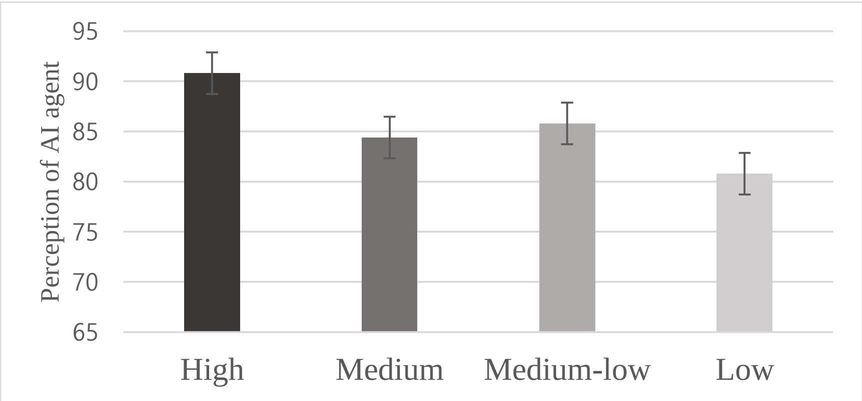

Figure 4. Effect of voice pitch condition on perception of smart speaker

Interestingly, males and females perceived the AI agent differently (Table 1). Figure 4 reveals that females perceive high pitched voice more positively than low pitched voice. However, males positively perceive high or low pitched voice while medium pitched voices were perceived less positively. To further analyze this effect, two-tailed t-test was conducted and males perceived low pitch condition significantly more positively than females ($t(8) = 2.73$, $p<0.03$). Specifically, the difference was largest in two subscales, anthropomorphism and animacy. While males perceived the AI agent as very human-like and lively, females perceived it as most machine-like of all conditions. This may be attributed to the tendency for people to anthropomorphize the AI agent with same gender more strongly (Eyssel et al., 2012). Although voice conditions were all in female voice, low voice may have been anthropomorphized more strongly by males since it is closer to male voice.

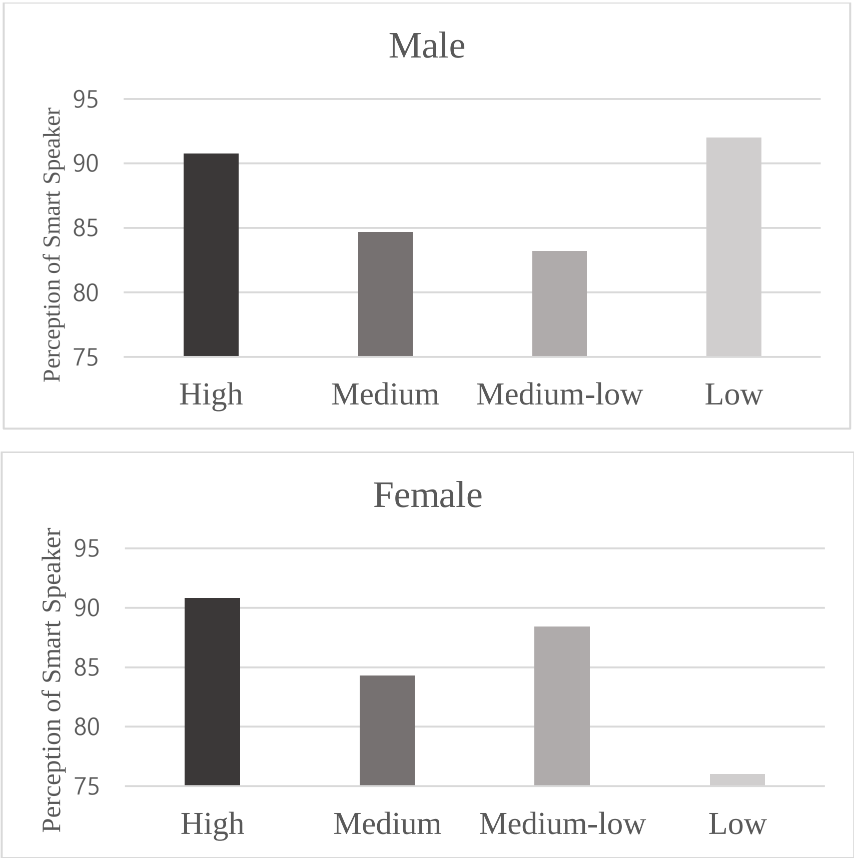

Figure 5. Effect of voice pitch condition on perception of smart speaker by gender

Table 1
Means and standard deviations of perception of smart speaker

	Condition	*M*	*SD*
All	High	90.80	9.92
	Medium	84.40	11.75
	Medium-Low	85.80	10.04
	Low	80.80	11.13
Male	High	90.75	8.22
	Medium	84.67	9.07
	Medium-Low	83.20	9.25
	Low	92.00	10.81
Female	High	90.83	11.69
	Medium	84.29	13.01
	Medium-Low	88.4	11.15
	Low	76.00	7.57

User Trust. There was a decline in the HCT score as the voice pitch decreases. High pitch condition was most trusted while low pitch condition was least trusted (Table 2). Human-Computer Trust scale (HCT) scores were compared between high and low conditions using two-tailed t-test. The test revealed that the two scores were not significantly different ($t(18) = 0.419$, p = n.s., $d = 0.187$). However, Cohen's d analysis showed that there is a small effect. One-way ANOVA was conducted to compare the means across the four conditions and the results were not statistically significant ($F(3, 36) = 0.098$, p = n.s.). The voice pitch condition and trust level were not correlated ($r = -.087$, p = n.s.).

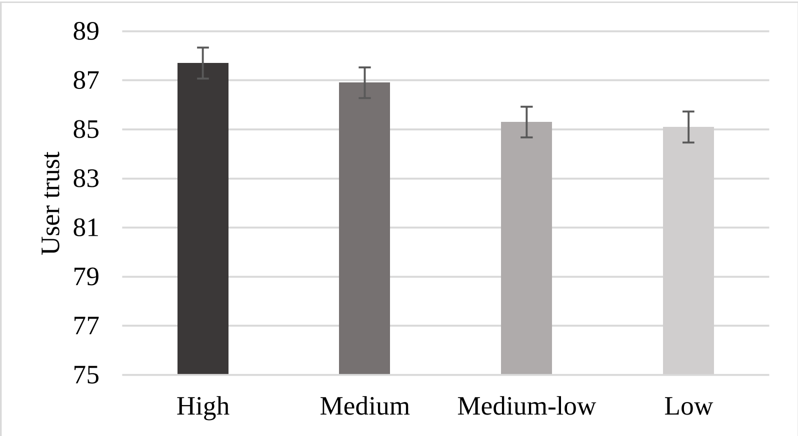

Figure 6. Effect of voice pitch condition on trust in smart speaker

Table 2
Means and standard deviations for user trust

Condition	*M*	*SD*
High	87.7	15.01
Medium	86.9	12.58
Medium-Low	85.3	9.99
Low	85.1	12.64

Trust Game. Low condition received the highest amount among all conditions (Table 3). Two-tailed t-test was conducted to compare the scores between high and low conditions. It was found that there is no statistically significant difference ($t(18) = -0.368$, p = n.s., $d = 0.443$). One-way ANOVA was conducted to compare the means across four conditions and the results were not statistically significant ($F(3, 36) = 0.29$, p = n.s.). The voice pitch condition and trust game amount were not correlated ($r = 0.041$, p = n.s.).

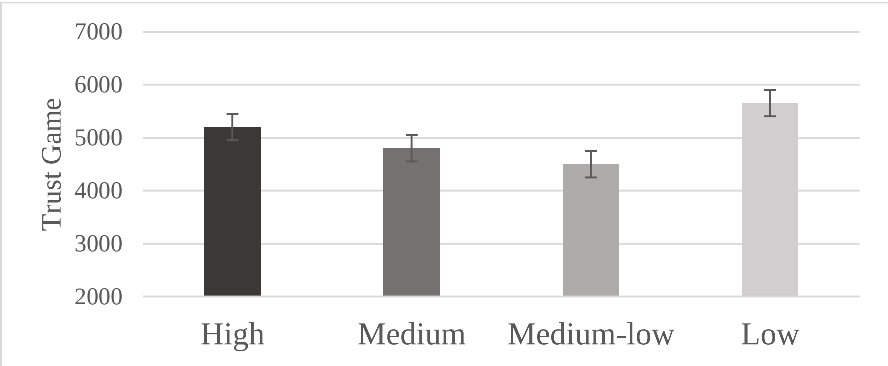

Figure 7. Effect of voice pitch condition on trust game values

Table 3
Means and standard deviations for trust measured by the trust game.

Condition	*M*	*SD*
High	5200	2201.01
Medium	4800	2820.56
Medium-Low	4500	3374.74
Low	5650	3180.23

Mediation Analysis. We conducted mediation analysis to examine mediation of perception of AI agent on the effect of voice pitch to user trust. For analysis, the voice pitch was coded as *high* = 1, *medium* = 2, *medium-low* = 3, and *low* = 4.

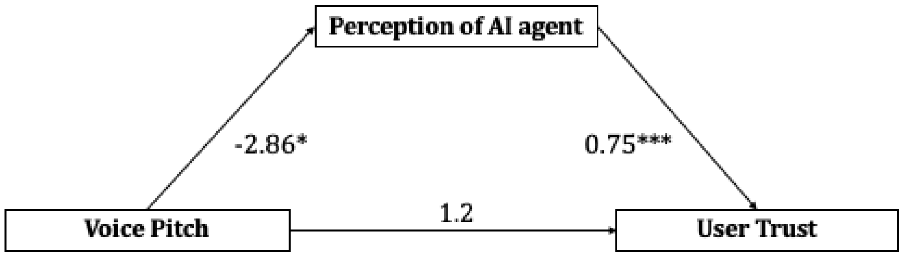

Figure 8. Results from mediation analysis (* *p*< .05; *** *p*< .001)

Table 4
Coefficient estimates for mediation model

	β	*SE*	*t*	*p*	CI (lower)	CI (upper)
X → M (a)	-2.86	1.45	-1.97	0.049	-5.54	0.08
M → Y (b)	0.75	0.14	5.44	0.000	0.46	0.99
X → Y (c)	1.20	1.35	0.89	0.374	-1.66	3.66
X → Y (c')	-2.14	1.11	-1.92	0.054	-4.34	0.05
X → M → Y	-0.94	1.91	-0.49	0.622	-4.56	2.92

We used bootstrapping procedures for the testing of the mediation effect. The effect of voice pitch on trust was fully mediated by perception of the AI agent. The regression of the voice pitch condition on trust was not significant (β = 1.20, p = n.s.). The regression of voice pitch condition on perception of AI agent was significant (β = -2.86, p = n.s.) and the regression of perception on trust was largely significant (β = 0.75, p< .001). The indirect effect, the effect of voice pitch condition on trust through perception of AI agent was marginally significant (β = -2.14, p = 0.054). These results indicate that the perception participants had mediated the effect of voice pitch of smart speaker on user trust.

Interview. All participants completed an interview at the conclusion of the experiment (*N*=40). Seven interview questions were asked. Five questions were about the interaction and their thoughts on the smart speaker. Two questions were about voice of the smart speaker.

Interaction and Thoughts. When asked what made them feel the smart speaker was human-like, only one participant responded that the smart speaker did not appear human-like. Eighty percent of the participants commented on social quality of the smart speaker, mentioning the word-chain game and small talk. Other 17.5 percent of the participants mentioned technical advancement, such as “understanding my words well” and “recommendations when I can’t decide.” Forty percent of the participants said that they can be friends with the smart speaker while 37.5 percent said that it is not possible. Fifteen percent claimed that they can become friends with more advances in technology and when the interaction is more fluid. Two participants said that they can become friends but it would be different than human friends. All but one participant said that they would like to have a smart speaker as an assistant at home.

The smart speaker used in the experiment led the interaction even when the participants did not ask any questions. We asked how the participants felt about such interaction. Seventy five percent of the participants had positive reaction. They said it is friendlier and easy to approach when the speaker talks first. They also mentioned it would be good to have such speaker when they are bored but annoying when they are busy.

Voice. When asked how they felt about the voice, 42.5 percent of the participants answered positively. They said it was calm, natural, and comfortable while 47.5 percent felt it was machine-like and artificial. Among them, 8 participants quoted other voice assistants such as Siri, mentioning it is average artificial voice as expected. For medium pitched voice, two participants said it was too bright. It was interesting that low voice pitch condition received only one participant gave positive comment about the voice.

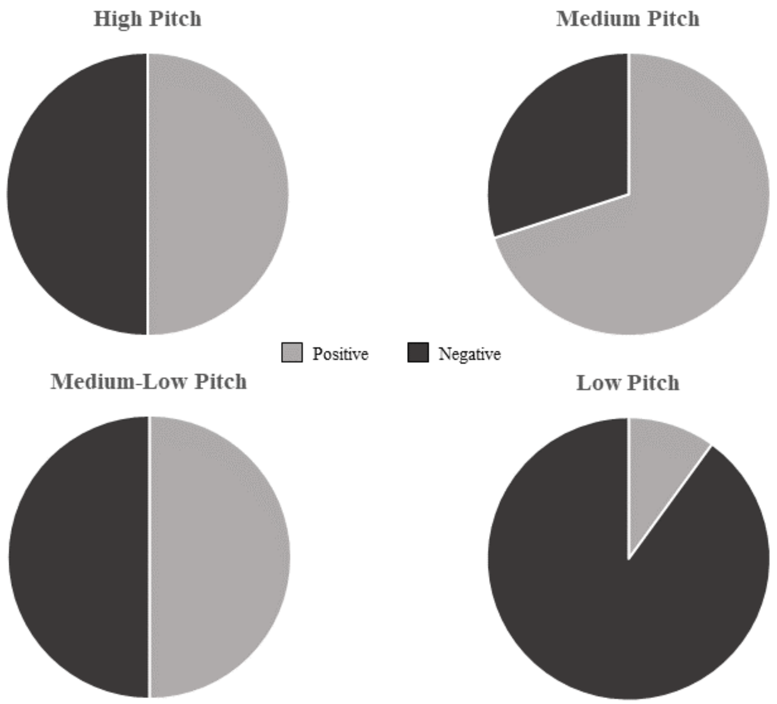

Figure 9. Positive vs. negative comment on voice of smart speaker

We asked how they would feel if the smart speaker had a gender-neutral voice. Twenty-five percent said they would be okay with it and 75 percent said they would not use it. Among those who did not want gender-neutral voice, six participants did not care which gender voice, but wanted a gendered voice. Five participants specifically wanted female voice, and two wanted male voice. Participants often commented that because gender-neutral voice do not exist in reality, it would sound more artificial and make them feel uncomfortable.

Observations. In Korean, there are two forms of speech: casual speech and formal speech. Casual speech is used between friends and in close relationships. Formal speech, on the other hand, is used in formal situations and between acquaintances. The smart speaker used formal speech in all conditions. Fifty-five percent of the participants used casual speech when talking to the smart speaker and 40 percent used formal speech. Two participants used formal speech at first, but changed to casual speech during small talk with the smart speaker. This may be because the participants felt closer to the smart speaker after disclosing personal information (e.g., sharing their favorite food or color).

During the interaction, many participants said “thank you” and “sorry,” treating the smart speaker as if human rather than a machine or robot. One participant even mentioned to the experimenter that the smart speaker is “adorable.” The participants asked personal questions to the speaker like they would with another person (e.g. “Do you like being a smart speaker?”, “Why do you like blue?”, and “How old are you?”).

4. Discussion

The results showed that participants perceived AI agent with high pitched voice more positive than the ones with low pitched voice. This effect is different depending on gender of the user. Males rated smart AI agent more positively when the voice is either high or low while females rated it better when the voice is high. The perception of the AI agent and user trust influence how much the users trust the AI agent and whether they would follow the AI agent’s suggestions. However, when trusting the AI agent in terms of monetary values, the users trusted low-pitched voice more. This is consistent with the results of previous literature. Low-pitched voice is more trusted in human-human interaction in situations involving money (O’connor & Barclay, 2017). Similarly, in human-agent interaction, low pitched voice was rated as more trustworthy. The results suggest that humans put trust in human-like agents as they do in other people. To further analyze the similarity between the two interactions (human-human and human-agent interaction), we conducted study 2. When two people interact, turn-taking is a central component for judgement about the speaker. People judge others based on the method way they participate in the conversation (Wiemann & Knapp, 1975). We manipulated interaction method (*active* vs. *passive*) in study 2 to examine how it influences perception of the AI agent and trust.

Chapter 3. Study 2

1. Hypotheses

In study 2, explored other influencing factors of trust in AI agents. We investigated how interaction with AI agent and user personality influences perceived anthropomorphism and trust. Active AI agents talk to the users even when not prompted. Therefore, we predicted it would be perceived as more human-like. We hypothesized that perception of the AI agent (anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety) would be more positive for active smart speaker than passive smart speaker. We also hypothesized that user trust would be higher for active AI agent than for passive AI agent. Similar to mediation analysis results of study 1, we predicted that perception of the AI agent will mediate the effect of interaction style on user trust. Prior research showed that those who are extroverted and emotionally stable are more likely to trust automation (Hoff & Bashir, 2015). Thus, we hypothesized that participants with higher extroversion and openness to experience would have more positive perception of AI agent and higher user trust.

2. Method

Participants. Participants were recruited online via Sona Systems. A total of 30 participants were recruited and 12 were female. All participants were undergraduate students (M_{age}= 20.4,SD = 1.96). They were provided with a written description of the experiment and a signed consent was obtained for each participant. The participants were randomly assigned to active or passive smart speaker condition (N = 15 for each condition).

Measures and Design. Four questionnaires were used in study 2. We continued to use Godspeed questionnaire (Bartneck, Kulic, & Croft, 2008), Human-Computer Trust scale (HCT) (Madsen & Gregor, 2000) and trust game (Berg, Dickhaut, & McCabe, 1995) for study 2.

User personality. As a personality measure, HEXACO Personality Inventory (HEXACO-PI) was included for this study (Lee & Ashton, 2004; Yoo, Lee, & Ashton, 2004). HEXACO-PI consists of six personality factors; Honesty-Humility (H), Emotionality (E), Extraversion (X), Agreeableness (A), Conscientiousness (C), and Openness to Experience (O). We used 100-item version of self-report form. Validated Korean version of the inventory was obtained from the authors' website with the permission from the author (hexaco.org/hexaco-inventory).

Procedure. Study 2 investigated how interaction with AI agent and user personality influences perception of AI agent and trust. There were two smart speaker conditions, active and passive. Active smart speaker interacted in the same manner as study 1. The speaker initiated and led the conversation with the participant. Passive smart speaker, on the other hand, functioned like the smart speaker we use commonly. It talked only when the user asked and the user said the activation word for the smart speaker to respond. The activation word was “Dooriya,” which was the speaker’s name. The voice of the speaker was the same for both conditions and was female voice. It was generated through an online text-to-speech engine (Naver Corp.). The participants were given the same study scenario as study 1. For those in passive speaker condition, task list was also provided to the participants to guide them what to talk about with the speaker. In addition, having a task list controlled for conversation topics between the conditions. The tasks were the same as study1, where the smart speaker demonstrates both assistive functions and social functions.

After the conclusion of the conversation with the smart speaker, the experimenter came back and asked the participant to fill out a survey on the tablet. The survey consisted of HCT questionnaire, Godspeed questionnaire, HEXACO-PI, and trust game. Then they were debriefed about the Wizard of Oz methodology and were thanked.

3. Results

Perception of the smart speaker. Interaction method did not induce difference in perception of AI agent. The mean score of the Godspeed questionnaire for active and passive conditions were compared using two-tailed t-test (see Table5 for means and SD). Although passive condition received more positive ratings, the scores were not significantly different between the two conditions ($t(28)=-0.34$, p = n.s., $d = 0.12$).

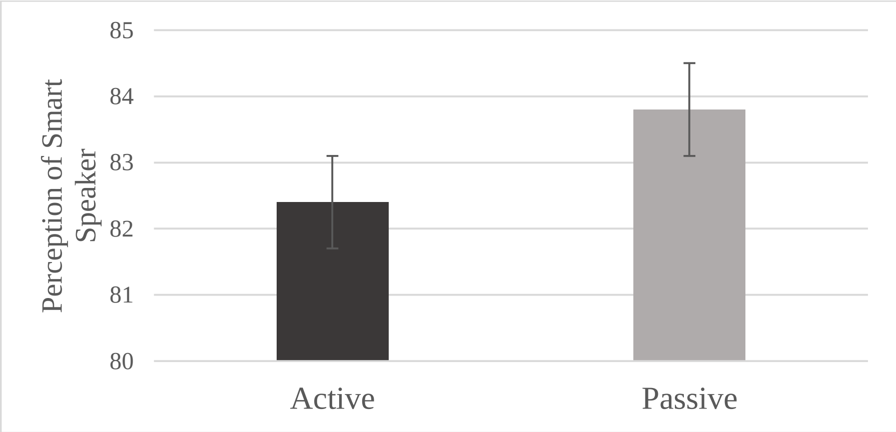

Figure 10. Effect of interaction method on perception of the smart speaker

This difference in perception of AI agent by condition was bigger in females than males. The difference in mean of Godspeed Questionnaire score between active and passive conditions in males was 0.23 while in female, it was 3.17.

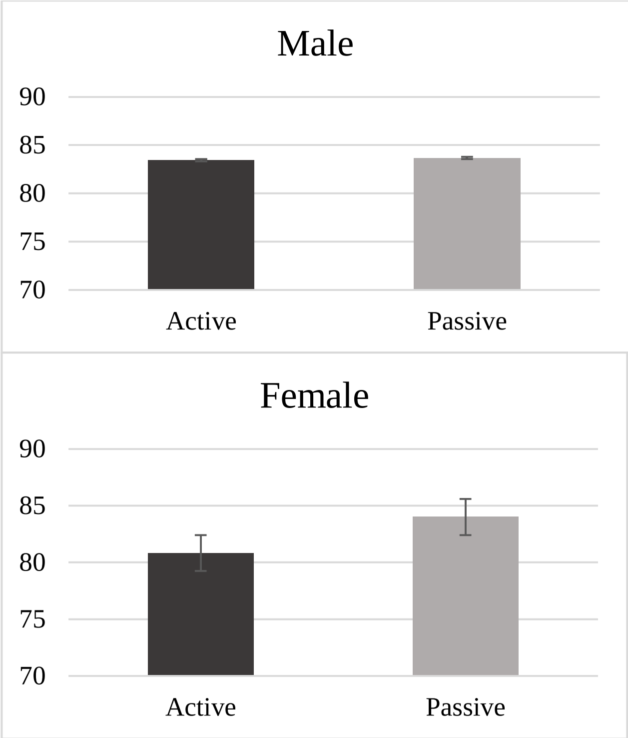

Figure 11. Effect of interaction method on perception of smart speaker by gender

Table 5
Means and standard deviations for perception of smart speaker by interaction method

	Condition	*M*	*SD*
All	Active	82.4	13.15
	Passive	83.80	9.32
Male	Active	83.44	16.93
	Passive	83.67	10.72
Female	Active	80.83	4.54
	Passive	84.00	7.69

User Trust. Active smart speaker was more trusted than the passive smart speaker (Table 6). Human-Computer Trust scale (HCT) scores between active and passive conditions were not significantly different when conducted two-tailed t-test ($t(28) = 0.163$, p = n.s., $d = 0.06$).

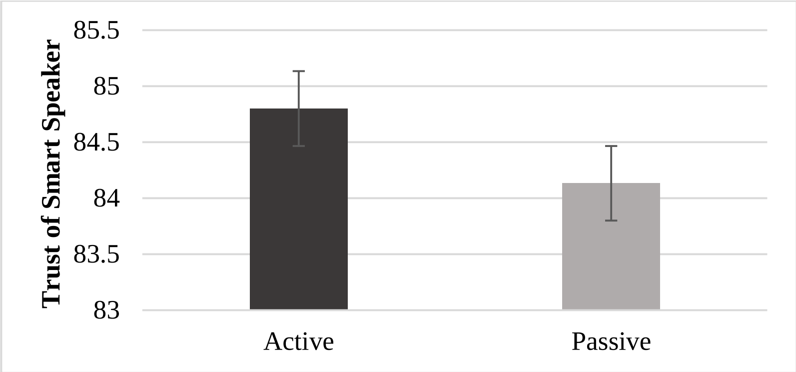

Figure 12. Effect of interaction style on user trust

Table 6
Means and standard deviations for user trust by interaction style

	Condition	*M*	*SD*
All	Active	84.80	12.15
	Passive	84.13	10.15
Male	Active	84.00	14.14
	Passive	84.67	11.60
Female	Active	86.00	9.51
	Passive	83.33	8.50

Similar to the perception ratings, females showed bigger difference in trust rating (2.67 in female, 0.67 in male). However, the effect was opposite, with active smart speaker rated as more trustworthy than passive smart speaker. Moreover, males were more trusting of passive smart speaker while females trusted active smart speaker more.

Trust Game. Active smart speaker received higher amount for trust game than passive smart speaker (see Table7 for means and SD). Two-tailed t-test was conducted to compare the scores between active and passive conditions. It was found that the difference between the two conditions is not statistically significant ($t(28) = 0.34$, p= n.s., $d = 0.139$).

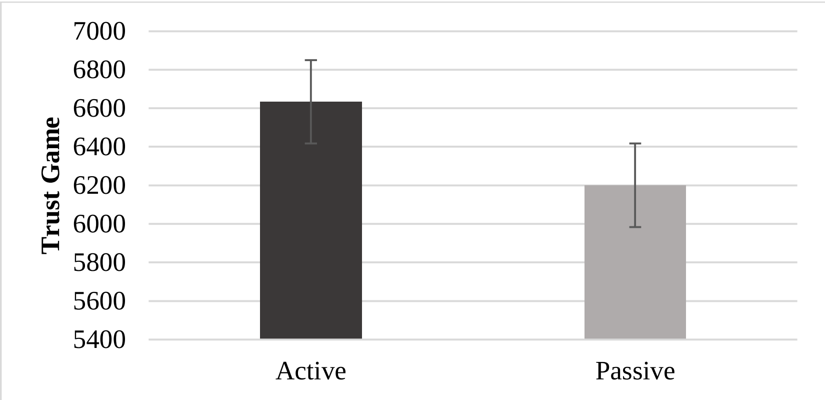

Figure 13. Effect of interaction method on trust game values

Table 7

Means and standard deviations for trust game by interaction style

	Condition	*M*	*SD*
All	Active	6633.33	3002.78
	Passive	6200.00	3913.35
Male	Active	6055.56	3186.34
	Passive	6222.22	4521.55
Female	Active	7500.00	2738.61
	Passive	6166.67	3188.52

User Trust and Trust Game. We performed multiple regression analysis to analyze the relationship between different components of trust. The correlation between subscales of HCT questionnaire (perceived reliability, perceived technical competence, perceived understandability, faith, and personal attachment) and trust game was analyzed. HCT scores and trust game values from study 1 and 2 were combined (N = 70). The coefficients revealed that trust game value increases with increase in perceived reliability, faith, and personal attachment. However, it decreases as perceived technical competence and perceived understandability score increases. The relationship, however, was not statistically significant.

Table 8

Results from regression analysis for HCT and trust game

	Trust Game			
Measure	*β*	SE	t	*p*
Perceived Reliability	112.39	176.60	0.636	0.527
Perceived Technical Competence	-29.43	154.78	-0.190	0.850
Perceived Understandability	-58.93	171.40	-0.344	0.732
Faith	134.75	145.23	0.928	0.357
Personal Attachment	73.35	107.01	0.685	0.496

Note. R^2 = 0.094; adjusted R^2 = 0.022; $F(5, 63) = 1.306$, $p = .273$

Mediation Analysis. We conducted mediation analysis to examine how perception of the smart speaker mediates the relationship between style of the smart speaker and user trust. For analysis, the smart speaker style was coded as *active* = 1, *passive* = 2.

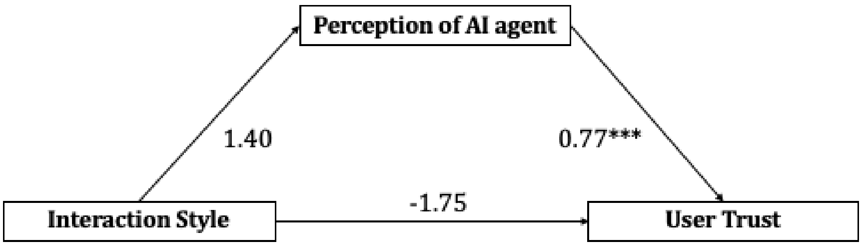

Figure 14. Results from mediation analysis (*** $p < .001$)

Table 9
Coefficient estimates for mediation model

	β	*SE*	*t*	*p*	CI (lower)	CI (upper)
X → M (a)	1.40	4.14	0.34	0.735	-6.27	9.97
M → Y (b)	0.77	0.11	6.76	0.000	0.53	1.01
X → Y (c)	-1.75	2.58	-0.68	0.499	-6.94	3.09
X → Y (c')	1.08	3.20	0.34	0.735	-5.05	7.68
X → M → Y	-0.67	4.06	-0.16	0.870	-8.64	7.49

We used bootstrapping method for the testing of the mediation effect. The effect of smart speaker style on trust was not mediated by perception of the smart speaker. The regression of the smart speaker style on trust was not significant (β = -1.75, p = n.s.) and the regression of style of smart speaker on perception of the smart speaker was not significant (β = 1.40, p = n.s.) The regression of perception on trust was largely significant (β = 0.77, p< .001). The indirect effect, the effect of voice pitch condition on trust through perception of the smart speaker was not significant (β = 1.08, p = n.s.). These results indicate that the perception of the smart speaker largely affects user trust. However, the style of the smart speaker does not affect perception or the trust for the speaker.

Personality. HEXACO-PI was scored following the guideline (Lee & Ashton, 2004; Yoo, Lee, & Ashton, 2004). We performed multiple regression analysis to test whether personality factors predict perception of the smart speaker and user trust. The results are presented in tables 9, 10 and 11. The analysis showed that honesty-humility is a significant predictor of trust game amount.

Table 10

Results from regression analysis for perception of AI agent

	Perception of AI agent							
	Model I[a]				Model II[b]			
Measure	β^c	SE	*t*	*p*	β^c	SE	t	*p*
Honesty-Humility (H)	-0.43	0.25	-1.72	0.09	-0.44	0.28	-1.58	0.12
Emotionality (E)	0.03	0.23	0.14	0.88	0.05	0.25	0.19	0.84
Extraversion (X)	0.22	0.24	0.92	0.36	0.08	0.29	0.29	0.77
Agreeableness (A)	-0.17	0.21	-0.82	0.41	0.00	0.25	0.00	0.99
Conscientiousness (C)	0.28	0.20	1.38	0.17	0.20	0.25	0.81	0.42
Openness to Experience (O)	0.17	0.20	0.84	0.40	0.14	0.21	0.67	0.50

Note. N = 30. [a]Model I: linear regression model including a single personality factor as an independent variable (R^2 = .096, .0007, .030,.024, .064, .025; adjusted R^2 = .064, -.035, -.005, -.011, .030, -.010; $F(1, 28)$ = 2.983, .020, .860, .677, 1.906, .715; for H, E, X, A, C, O, respectively). [b]Model II: multiple regression model including all six personality factors as independent variables (R^2 = .177; adjusted R^2 = -.038; $F(6, 23) = .822$, $p = .564$) [c]β: standardized coefficient

Table 11

Results from regression analysis for user trust

	User trust							
	Model I[a]				Model II[b]			
Measure	β[c]	SE	*t*	*p*	β[c]	SE	t	*p*
Honesty-Humility (H)	-0.45	0.24	-1.85	0.07	-0.36	0.26	-1.36	0.18
Emotionality (E)	-0.23	0.22	-1.06	0.29	-0.35	0.24	-1.47	0.15
Extraversion (X)	0.21	0.23	0.91	0.36	0.10	0.27	0.38	0.70
Agreeableness (A)	-0.25	0.20	-1.19	0.24	-0.27	0.23	-1.12	0.27
Conscientiousness (C)	0.22	0.20	1.11	0.27	0.16	0.23	0.70	0.49
Openness to Experience (O)	-0.00	0.20	-0.02	0.98	-0.12	0.20	-0.59	0.55

Note. *N* = 30, [a]Model I: linear regression model including a single personality factor as an independent variable (R^2 = .109, .039, .029, .049, .042, .000; adjusted R^2 = .077, .004, -.005, -.011, .008, -.036; $F(1, 28)$ = 3.43, 1.128, .840, 1.433, 1.233, .0004; for H, E, X, A, C, O, respectively). [b]Model II: multiple regression model including all six personality factors as independent variables (R^2 = .242; adjusted R^2 = .044; $F(6, 23) = 1.223$, $p = .331$) [c]β: standardized coefficient

Table 12
Results from regression analysis for trust game

	Trust game							
	Model I[a]				Model II[b]			
Measure	β^c	SE	*t*	*p*	β^c	SE	t	*p*
Honesty-Humility (H)	-204.89	72.07	-2.84	.008**	-206.79	80.53	-2.56	0.01*
Emotionality (E)	-66.25	69.96	-0.94	0.35	-44.51	73.89	-0.60	0.55
Extraversion (X)	-61.56	74.03	-0.83	0.41	-57.03	84.89	-0.67	0.50
Agreeableness (A)	14.34	66.82	0.21	0.83	30.43	73.09	0.41	0.68
Conscientiousness (C)	-9.67	65.84	-0.14	0.88	15.60	72.85	0.21	0.83
Openness to Experience (O)	4.93	62.71	0.07	0.93	19.78	62.68	0.31	0.75

Note. *N* = 30, [a]Model I: linear regression model including a single personality factor as an independent variable (R^2 = .224, .031, .024, .002, .000, .000; adjusted R^2 = .196, -.004, -.011, -.011, -.035, -.035; $F(1, 28)$ = 8.082, .897, .692, .046, .022, .006; for H, E, X, A, C, O, respectively).[b]Model II: multiple regression model including all six personality factors as independent variables (R^2 = .272; adjusted R^2 = .083; $F(6, 23)$ = 1.435, p = .244), [c]β: standardized coefficient

Observations. Identical to study 1, the smart speaker used formal speech in all conditions. All participants in passive condition used casual speech, while half of the participants in active condition used casual speech and other half used formal speech. In passive condition, the participants have to use the activation word “Dooriya,” which is calling “Doori” in casual speech. This may have contributed to the usage of casual speech.

The participants in active condition often used “Thank you” or “I’m sorry” while speaking to the smart speaker, treating the speaker as human than a machine. The participants in passive condition rarely treated the speaker as human and did not use above mentioned expressions.

4. Discussion

The results of study 2 revealed that interaction method of the smart speaker is not correlated with perception of AI agent or the user trust. Passive condition was perceived more positively than active condition, while active condition was more trusted. Mediation analysis revealed that perception of AI agent has a significant effect on user trust. When we looked at individual differences and how personality affects the dependent variables, honesty-humility factor significantly predicted trust game value. Honesty-humility factor and trust game value had a negative correlation. Individuals with high honesty-humility score “avoid manipulating others for personal gain” and tend to be "genuine in interpersonal relations" (Lee & Ashton, 2004). Thus, those with high honesty-humility score may not perceive smart speaker as genuine as human interaction it is an AI agent. They also may have given less money to the smart speaker in trust game because they are uninterested in wealth and high social status.

Chapter 4. Conclusion

In study 1, we manipulated voice pitch of smart speaker to examine its correlation with perception of the AI agent and trust. Our prediction that perception of AI agent would increase with increase in voice pitch was supported. AI agent was more positively perceived as the voice pitch increased. AI agent was rated more anthropomorphic, animate, likeable, intelligent, and safe when the voice pitch was high. Hypothesis where user trust would increase with increase in voice pitch was supported as well. User trust increased with increase in voice pitch. The AI agent with higher voice pitch was more trusted compared with low voice pitched AI agent. Perception of the AI agent fully mediated the influence of voice pitch on user trust. Increase in voice pitch positively influenced the perception of the AI agent, which positively affected user trust.

In study 2, we manipulated interaction method of the smart speaker to explore its effect on perception of the AI agent and trust and investigated how user personality effects the variables. First hypothesis was not supported. AI agent was more positively perceived when it was passive compared to when it was active. AI agent was rated more anthropomorphic, animate, likeable, intelligent, and safe when it responded only when prompted. Our prediction that user trust would be higher for active smart speaker than for passive smart speaker was supported. User trust was higher for AI agent that initiates conversation. Positive perception of the AI agent increased user trust of the user, mediating the relationship between interaction style and trust. Our hypothesis that user's extroversion and openness to experience will positively influence the perception of AI agent and user trust was not supported. Extroversion and openness to experience did not significantly influence perception of the AI agent or trust. However, honesty-humility had a negative impact on trust.

The results of studies 1 and 2 suggest that numerous factors influence user's trust in AI agents. Voice pitch and interaction style, although are main components of voice user interface, are not often considered in designing and manufacturing of AI agents. Factors that are overlooked do affect how users perceive and accept the technology. AI agents made with careful consideration of these factors will guide the users to maintain appropriate level of trust and benefit from using them.

Chapter 5. General Discussion

This study aimed to explore the influencing factors of trust in AI agents with voice user interface. We used Wizard of Oz design where the experimenter chooses adequate dialogue from the script while listening to the participants. It enabled us to conduct a controlled and natural experiment. As a result, users rated AI agent with higher voice pitch more human-like, better, and more trustworthy. More social AI agent was more trusted than the passive one. In both studies 1 and 2, perception of AI agent mediated trust, where increase in perception rating also increased trust level. The results of the study suggest that individual characteristics should be considered in human-robot interaction. The findings also suggest that human-agent interaction is not far different from human-human interaction. As people treat AI agents as humans, the interaction being social is inevitable. The importance of social AI agents is emphasized with growing single-person household population.

Single-person household have appeared as a common household structure. In Korea, the percentage of single-person household has almost doubled from 15.5 percent in 2000 to 29.3 percent in 2018 (KOSIS, 2018). This number will continue to increase with projected growth of 43 percent by 2030. This change in household structure is not limited to Korea but is rather a global trend. OECD expects significant increase in the number of one-person households in all OECD countries. The largest projected percent increase is 75 percent for France, which OECD attributes to the ageing population (Stevens, Schieb, & Gibson, 2011).

Individuals of single-person households often lack social interaction, affecting psychological well-being. Age is a significant predictor of psychological well-being in single-person household. Elderly persons who live alone have higher level of depressive symptoms and loneliness (Antonacopoulos&Pychyl, 2010; Dean et al., 1992; Russell & Taylor, 2009). However, with high levels of social support, those who live alone feel significantly less lonely than individuals with low social support (Antonacopoulos&Pychyl, 2010). In addition, those who received more social support from friends showed lower levels of depression than those who did not (Potts, 1997).

Following the growth of one-person household, adoption of conversational agents has increased. Smart speakers, being small and cost efficient, has been implemented in abundant number of homes to fill the gap of lacking social interaction. This global trend is prospected to continue and experience exponential growth. Moreover, rapid advances in technology and natural language processing have opened options for people to adopt a smart speaker or small human-like robots at home. Outside home, people often interact with artificial intelligence on telephone and chat bots. With increasing number AI agents of varying type, we will continue to encounter and interact with them. Thus, understanding the influencing variables of the interaction is crucial.

In 2018, Google presented the recording of an actual phone call made by Google Assistant, named Duplex. Duplex called a hair salon and booked an appointment. The voice was incredibly natural and Duplex understood the nuances of conversation. It even used casual speech and said “mm-hmm.” The person on the other side of the phone did not know they were interacting with an AI agent. Although this demonstration displayed how advanced AI agent is nowadays and what it is capable of doing, many expressed strong discomfort. They commented that Duplex is “creepy,” “horrifying,” “unethical,” and “deceiving.” Google Duplex serves as an example of too much “human-ness” in AI agents inducing discomfort and repulsion. It emphasizes the importance of understanding what users want and what factors affect how users adopt and approve AI agents. Lack of understanding will not only bring repulsion, but also disuse of AI agents and even opposition against AI technology.

Limitations and Implications

Current study has limitations that remains to be further investigated in future studies. First, the study participants were all young adults. Previous research suggests that different age groups, especially older adults respond and interact differently with AI agents. Further research is needed to explore the difference in perception and trust across different age groups. Second, the study was administered in experimental setting. The interaction with the AI agent may be different if the participants are at home or in a more comfortable situation. Future research with smart speaker at a familiar location and extended period of usage will bring more understanding of the current findings. Another limitation is that the measures used in the study are self-reported. Self-report data combined with behavioral measures will strengthen the findings.

Additional research on influencing factors of human-robot interaction can be investigated in the future. The results of this study can be extended to investigation of how voice pitch and interaction method influences trust in AI agents with mistakes. Along with trust, research addressing how users perceive the AI agents (e.g. user's expectation, approachability) is needed. Moreover, user-centered AI agents where the AI agents are personalized to match the characteristics of the user should be considered.

Advancement in technology has brought us this far where imaginations from Sci-fi movies are right here at our home. Better understanding of people's interaction and expectation on the AI agents will bring convenience and better quality of life.

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Appendix

Appendix 1: Godspeed Questionnaire (Bartneck, Kulic, & Croft, 2008)

사용한 AI 스피커의 인상을 다음 항목에 대해 평가해주세요.

가짜 같은	1	2	3	4	5	자연스러운
기계적인	1	2	3	4	5	인간 같은
의식이 없는	1	2	3	4	5	의식이 있는
인공적	1	2	3	4	5	생물적
죽어있는	1	2	3	4	5	살아있는
활기가 없는	1	2	3	4	5	생기있는
기계적인	1	2	3	4	5	유기적인
인공적인	1	2	3	4	5	생물적인
기력이 없는	1	2	3	4	5	상호작용을 하는
무관심한	1	2	3	4	5	반응을 하는
싫음	1	2	3	4	5	좋음
친해지기 어려운	1	2	3	4	5	친해지기 쉬운
불친절한	1	2	3	4	5	친절한
불쾌한	1	2	3	4	5	유쾌한
형편없는	1	2	3	4	5	좋은
무능한	1	2	3	4	5	유능한
무지한	1	2	3	4	5	박식한
무책임한	1	2	3	4	5	책임감 있는
무식한	1	2	3	4	5	지적인
어리석은	1	2	3	4	5	현명한
불안한	1	2	3	4	5	안정된
냉정한	1	2	3	4	5	동요되는
평온한	1	2	3	4	5	놀란

Appendix 2: Human Computer Trust (HCT) Scale (Madsen & Gregor, 2000)

AI 스피커에 대해 평가해주세요.

1. 이 AI 스피커는 언제나 내가 결정을 내리는 데에 필요한 조언을 해준다

전혀 동의하지않음 1 2 3 4 5 매우 동의함

2. 이 AI 스피커의 작동은 안정적이다

전혀 동의하지않음 1 2 3 4 5 매우 동의함

3. 이 AI 스피커는 다른 시간의 같은 조건에서 똑같이 반응한다

전혀 동의하지않음 1 2 3 4 5 매우 동의함

4. 나는 이 AI 스피커가 제대로 작동할 것이라고 믿을 수 있다

전혀 동의하지않음 1 2 3 4 5 매우 동의함

5. 이 AI 스피커는 문제를 지속적으로 분석한다

전혀 동의하지않음 1 2 3 4 5 매우 동의함

6. 이 AI 스피커는 결정에 도달하기 위해 적절한 방법을 사용한다

전혀 동의하지않음 1 2 3 4 5 매우 동의함

7. 이 AI 스피커는 어떤 문제에 대한 지식을 보유하고 있다

전혀 동의하지않음 1 2 3 4 5 매우 동의함

8. 이 AI 스피커는 유능한 사람이 제시할만한 정도의 조언을 제공한다

전혀 동의하지않음 1 2 3 4 5 매우 동의함

9. 이 AI 스피커는 내가 입력한 정보를 알맞게 사용한다

전혀 동의하지않음 1 2 3 4 5 매우 동의함

10. 이 AI 스피커는 어떤 문제에 대답을 제시하기 위해 이용할 수 있는 모든 지식과 정보를 사용한다

전혀 동의하지않음 1 2 3 4 5 매우 동의함

11. 나는 이 AI 스피커가 어떻게 행동할지 이해했기 때문에 다음에 이 시스템을 이용할 때 어떤 일이 일어날지 알고 있다

전혀 1 2 3 4 5 매우
동의하지않음 동의함

12. 나는 이 AI 스피커가 내가 내려야 할 결정에 어떻게 도움을 줄지 이해하고 있다

전혀 1 2 3 4 5 매우
동의하지않음 동의함

13. 나는 이 AI 스피커가 어떻게 작동하는지 정확히 알지는 않아도 문제에 대해 결정을 내릴 때 이 AI 스피커를 이용할 줄 안다

전혀 1 2 3 4 5 매우
동의하지않음 동의함

14. 이 AI 스피커가 하는 일은 이해하기 쉽다

전혀 1 2 3 4 5 매우
동의하지않음 동의함

15. 다음에 이 AI 스피커를 이용할 때 AI 스피커에게서 필요한 조언을 받기 위해 어떻게 해야할지 알고 있다

전혀 1 2 3 4 5 매우
동의하지않음 동의함

16. 나는 이 AI 스피커가 제공하는 조언이 맞는지 확실치않아도 그 조언을 믿을 것이다

전혀 1 2 3 4 5 매우
동의하지않음 동의함

17. 나는 어떤 결정에 대해 불확실하다면 나 자신보다 이 AI 스피커를 믿을 것이다

전혀 1 2 3 4 5 매우
동의하지않음 동의함

18. 내가 어떤 결정에 대해 불확실하다면 이 AI 스피커가 적절한 조언을 해줄 것이라는 믿음이 있다

전혀 1 2 3 4 5 매우
동의하지않음 동의함

19. 이 AI 스피커가 특이한 조언을 해줄 때 나는 이 조언이 맞다고 자신할 수 있다

전혀 1 2 3 4 5 매우
동의하지않음 동의함

20. 나는 이 AI 스피커가 어려운 문제를 해결할 수 있을 것이라고 기대할 이유가 없지만 그래도 그럴 것이라고 생각한다

전혀 1 2 3 4 5 매우
동의하지않음 동의함

21. 나는 이 AI 스피커가 사용 불가능하고 내가 더 이상 사용할 수 없게 되면 상실감을 느낄 것이다

전혀 동의하지않음	1	2	3	4	5	매우 동의함

22. 나는 이 AI 스피커를 사용하는 것에 애착을 느낀다

전혀 동의하지않음	1	2	3	4	5	매우 동의함

23. 나는 나의 의사결정방식에 이 AI 스피커가 잘 맞는다고 생각한다

전혀 동의하지않음	1	2	3	4	5	매우 동의함

24. 나의 의사결정에 이 AI 스피커를 사용하는 것이 좋다

전혀 동의하지않음	1	2	3	4	5	매우 동의함

25. 나는 이 AI 스피커를 사용하여 의사결정을 하는 것이 개인적으로 좋다

전혀 동의하지않음	1	2	3	4	5	매우 동의함

Appendix 3: HEXACO Personality Inventory (Yoo, Lee, & Ashton, 2004)

제시되는 문장을 잘 읽고 그 문장에 얼마나 동의하는지를 표시해 주시기 바랍니다. 동의정도는 다음 척도를 사용하여 나타내어 주십시요.

5 = 매우 그렇다
4 = 그런 편이다
3 = 중간 정도
2 = 그렇지 않은 편이다
1 = 전혀 그렇지 않다

1	미술관에 가는 것을 지루하게 느낀다.
2	사무실이나 방을 매우 자주 청소한다.
3	나를 부당하게 대우한 사람에게도 큰 원한을 품지 않는 편이다.
4	전반적으로 내 자신에 대해 만족하는 편이다.
5	기상이 나쁜 날씨에 비행기 여행을 하게 된다면 겁이 날 것이다.
6	내가 싫어하는 사람에게서 얻어내고자 하는 것이 있으면, 그 사람에게도 매우 친한 것처럼 행동할 것이다.
7	다른 나라의 역사와 정치를 배우는 것에 관심이 많다.
8	일을 할 때 나는 야심찬 목표를 세운다.
9	나는 가끔씩 다른 사람을 너무 비판적으로 평가한다는 얘기를 듣는다.
10	단체 모임에서 나의 의견을 잘 나타내지 않는 편이다.
11	때때로 사소한 것에 대해 지나치게 걱정을 한다.
12	나는 잡히지 않을 자신만 있으면 남의 돈 몇 천만원쯤은 훔칠 수도 있다.
13	창의성을 요구하는 직업보다는 그냥 일상적 일과를 수행하는 직업을 갖고 싶다.
14	오류를 찾아내기 위해 내가 한 일을 반복적으로 점검하는 편이다.
15	사람들은 종종 내가 너무 고집이 세다고 말한다.
16	다른 사람들과 잡담하는 것을 좋아하지 않는다.
17	내가 고통스럽고 힘들 때 나를 위로해 줄 수 있는 사람이 꼭 필요하다.
18	많은 돈을 버는 것이 내 인생에서 그다지 중요하지 않다.

19 급진적 사상에 관심을 갖는 것은 시간 낭비일 뿐이다.

20 나는 주의깊게 생각하기보다는 순간적 기분에 따라 결정하는 편이다.

21 내가 화를 잘 내는 편이라는 얘기를 자주 듣는다.

22 나는 언제나 원기왕성하다.

23 다른 사람이 우는 것을 보면 나도 울고 싶어진다.

24 나는 보통사람이며, 남들보다 특별히 더 우월하다고 생각하지 않는다.

25 시집을 읽으며 시간을 보내는 일은 거의 없다.

26 막판에 서두르는 것을 피하기 위해 미리 계획을 세우는 편이다.

27 다른 사람이 나를 괴롭혔더라도 신경쓰지 않고 그냥 용서해주는 편이다.

28 내 성격의 어떤 면은 사람들이 좋아할만 하다고 생각한다.

29 위험이 수반되는 직업을 갖는 것도 개의치 않을 것이다.

30 승진이나 월급인상에 도움이 된다하더라도 상사에게 아부를 하지 않을 것이다.

31 여러 다른 지역의 지도를 보는 것을 즐긴다.

32 정한 목표를 이루기 위해 내 자신을 매우 심하게 다그치는 편이다.

33 나는 다른 사람의 실수를 불평없이 그냥 받아들이는 편이다.

34 단체에서 나는 다른 사람의 눈치를 보지않고 내 의견을 적극적으로 말한다.

35 다른 사람에 비해 쓸데없는 걱정을 하지 않는 편이다.

36 만일 내가 금전적으로 어려운 상태에 있으면, 장물(훔친물건)을 싸게 살 수 있는 방법을 알아보고 싶은 유혹을 느낄 것이다.

37 나는 소설, 음악, 그림 등의 예술작품을 창조하는 것을 좋아하는 편이다.

38 일을 할 때 사소한 부분에는 크게 신경을 안쓰므로 실수가 잦은 편이다.

39 내 의견이 다른 사람들과 다를 때 내 의견만을 고집하지 않는다.

40 나는 같이 얘기할 수 있는 사람이 주변에 많이 있는 것을 좋아한다.

41 다른 사람들의 정서적 지원이 없더라도, 나는 어떤 어려운 상황도 잘 헤쳐나갈 수 있다.

42 나는 부자 혹은 상류층 사람들이 사는 동네에 살고 싶다.

43 나는 관습에 얽매이지 않은 관점을 가진 사람을 좋아한다.

44 행동하기 전에 깊게 생각하지 않기 때문에 실수를 많이 저지른다.

45 어떤 사람이 나를 기분 나쁘게 대해도 화를 잘 내지 않는다.

46 나는 거의 매일 명랑하고 낙천적인 편이다.

47 친한 사람이 불행을 겪는다면, 그 사람의 고통을 내 것처럼 느낄 것이다.

48 다른 사람이 나를 높은 사람처럼 대접하면 좀 불편해진다.

49 기회만 있다면 클래식 음악회에 가보고 싶다.

50 다른 사람들이 내 방이나 책상이 지저분하다고 가끔씩 놀린다.

51 나를 단 한번이라도 속였던 사람에 대해서는 언제나 의심을 품을 것이다.

52 나는 별로 인기가 없는 편이라고 느낀다.

53 위험한 상황에 처하면 다른 사람보다 무서움을 많이 탄다.

54 어떤 사람에게서 얻어낼 것이 있으면, 싫더라도 그 사람의 비위를 맞추어 줄 것이다.

55 과학과 기술의 역사에 관한 책을 읽는 것이 지루하게 느껴진다.

56 목표를 세우고 나서도 종종 나는 그것을 달성하지 못한채 끝낼 때가 있다.

57 다른 사람을 판단하는데 있어서 나는 매우 관대한 편이다.

58 나는 종종 내가 속한 집단의 대변인 역할을 한다.

59 스트레스나 불안으로 인한 불면증을 경험한 적이 거의 없다.

60 나는 많든 적든 뇌물은 받지 않을 것이다.

61 풍부한 상상력을 가지고 있다는 말을 듣곤한다.

62 시간이 오래 걸리더라도 나는 항상 일을 정확하게 마무리하고자 한다.

63 누군가 내 의견이 틀렸다고 말하면, 나는 즉각 그 사람과 논쟁을 시작할 것이다.

64 주로 혼자 하는 일보다는 다른 사람들과 적극적으로 상호작용하는 일을 더 좋아한다.

65 걱정거리가 있으면 다른 사람에게 그 걱정거리를 털어놓고 상의하고 싶다.

66 나는 내가 매우 비싼 최고급 승용차를 타고 가는 모습을 사람들에게 보여주고 싶다.

67 나는 내가 약간 괴짜라고 생각한다.

68 나는 충동적으로 행동하지 않는다.

69 나는 다른 사람들보다 화를 잘 내지 않는 편이다.

70 나는 종종 사람들로부터 좀 더 활달해질 필요가 있다는 소리를 듣는다.

71 친한 사람과 오랫동안 떨어져 있어야 한다면 이별의 순간에 매우 슬픈 감정을 느낄 것이다.

72 나는 보통사람들보다 더 존경을 받을 만하다고 생각한다.

73 나는 가끔 바람에 흔들리는 나뭇잎을 바라보며 시간을 보내는 것을 좋아한다.

74 어떤 일을 할 때, 나는 때때로 너무 무계획적으로 하기 때문에 어려움을 겪는다.

75 나를 불쾌하게 했던 사람을 완전히 용서하고 없었던 일로 하기는 어렵다.

76 나는 가끔 하찮은 인간이라고 생각할 때가 있다.

77 굉장히 위급한 상황에 처해도 공포에 질리지 않는다.

78 무언가를 청탁하기 위해, 어떤 사람을 좋아하는 척 하지는 않을 것이다.

79 백과사전을 훑어보면서 시간을 보낸 적이 거의 없다.

80 나는 살아가는데 요구되는 최소한의 일만을 하면서 살고 싶다.

81 어떤 사람이 계속해서 실수를 저질러도 나는 싫은 소리를 잘 하지 않는다.

82 여러 사람 앞에서 발표할 때면 어색함을 느낀다.

83 중요한 결과를 기다릴 때면 걱정을 매우 많이 하는 편이다.

84 잡히지 않는다는 보장만 있으면, 위조지폐를 사용하고 싶은 유혹을 느낀다.

85 나는 예술적 또는 창의적 타입과는 거리가 멀다.

86 사람들이 종종 나를 완벽주의자라고 한다.

87 내의견이 옳다는 생각이 들면, 다른사람과 잘 타협하지 못하는 편이다.

88 새로운 환경에서 내가 제일 먼저하는 일은 친구를 사귀는 것이다.

89 내 문제에 대하여 다른 사람과 거의 상의하지 않는다.

90 비싸고 호화로운 명품을 갖고 싶어한다.

91 철학을 애기하는 것은 나에게 지루한 일이다.

92 나는 계획에 따라 행동하기보다는 지금 당장 맘에 내키는 일을 하는 것을 더 좋아한다.

93 다른 사람이 내 기분을 상하게 하면, 화를 잘 참지 못한다.

94 나는 다른 사람에 비해 별로 생기가 없고 활동적이지 않다.

95 대부분의 사람들이 매우 감상적으로 되는 상황에서도 나는 별로 감정적 동요를 느끼지 않는 편이다.

96 다른 사람들이 나를 높은 지위를 가진 중요한 사람으로 대접해 주기를 바란다.

97 불행한 사람들을 보면 동정과 연민을 느낀다.

98 나는 도움이 필요한 사람들을 위해 기부를 많이 하는 편이다.

99 내가 싫어하는 사람들한테는 아무렇지도 않게 해를 입힐 수도 있다.

100 사람들은 나를 매정하다고 생각한다.

국문 초록

인공지능의 발달은 단순한 알고리즘을 따라 움직이는 것을 넘어 사회적 에이전트의 등장으로 이어졌다. 스마트폰과 가전기기에 대화를 통한 상호작용이 가능한 인공지능 비서가 심어져 일상에서 흔히 사용되고 있다. 사용자들은 인공지능을 사람과 같이 대하는 경향이 있다. 따라서, 기술의 발달과 더불어 사람들이 인공지능 에이전트와 어떻게 상호작용하는지에 대한 연구의 필요성이 대두되고 있다. 본 연구는 오즈의 마법사 방법론을 사용하여 인공지능 에이전트와의 상호작용에서 신뢰에 영향을 미치는 요인을 탐구하고자 하였다. AI (Artificial Intelligence) 스피커를 인공지능 에이전트의 대표로 선정하여 이를 통해 연구를 진행하였다.

실험1에서는 목소리의 음고저 (pitch)를 다양하게 하여 인공지능에 대한 인식과 신뢰도에 미치는 영향을 살펴보았다. 실험에서 사용된 상호작용 과제는 일상적인 수다, 일정 관리 및 예약, 끝말잇기, 그리고 일기예보로 이루어져있었다. 사람들은 인공지능의 목소리가 낮을 때보다 높을 때 더욱 긍적적으로 인식하였고, 신뢰도 또한 목소리가 높아질수록 낮아지는 성향을 보였다. 그러나 경제적인 상황에서의 신뢰도는 목소리가 낮을수록 더욱 신뢰도가 높아지는 경향이 있었다.

실험2에서는 실험1과 같은 과제를 사용하여 상호작용 방법 (능동적 vs. 수동적)과 사용자의 성격특성이 인공지능에 대한 인식과 신뢰

도에 미치는 영향을 살펴보았다. 먼저 말을 걸어주는 인공지능 (능동적 조건)에 비해 질문을 해야 대답을 하는 인공지능 (수동적 조건)이 더욱 긍정적으로 인식되었으나 신뢰도는 더욱 높게 나타났다. 경제적인 상황에서도 능동적인 인공지능이 수동적인 인공지능보다 더욱 신뢰된다는 결과가 나타났다. 사용자의 성격은 정직/겸손 요인이 경제적 신뢰도에 유의미한 부적상관을 보이는 것으로 나타났다. 실험1과 실험2 모두에서 인공지능에 대한 인식은 신뢰도에 매개효과를 가지는 것으로 나타났다.

본 실험은 인공지능에 대한 인식과 신뢰도에 영향을 미치는 요인을 알아봄으로써 사람과 인공지능과의 상호작용에 대한 이해를 증진하고, 인공지능과 로봇 연구에서의 사회과학적 접근의 가치를 제시한다는 의의를 갖는다.

주요어: 신뢰, 사람-인공지능 상호작용, 인공지능

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