# EMPATHETIC AI AND CONSUMER BEHAVIOR

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## ABSTRACT OF THE THESIS

Empathetic AI and Consumer Behavior
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Consumers' rapid adoption of artificial intelligence (AI) such as virtual agents or smart assistants has led to increased collection of data that could be leveraged to shape consumer experience in unique ways. As this technology becomes more in tune with consumers' needs and preferences through biometrics and emotion detection, referred to as affective computing, AI smart assistants' possible influence on consumer behavior may be significant. If AI is able to communicate accurate detection of a consumer's emotion, it could assist consumers in making better decisions, but also might have real impact as an influencer. However, this level of personalization from a device has the potential to create a privacy concern among consumers. To mitigate this privacy-personalization paradox it is important to manage consumers' sense of vulnerability and make them feel special in their interactions with AI smart assistants. One potential mechanism to put consumers at ease is through empathetic interaction with AI smart assistants, known as artificial empathy. This thesis study tested human-computer interactions with a simulated AI smart assistant that detected a user's frustrated emotion in strong empathetic and weak empathetic conditions to determine whether these factors affected consumers' perceptions of the technology and openness to recommendations from the technology. Quantitative methods were used by administering surveys depicting a simulated conversation between subjects (potential consumer) and the AI smart assistant. This work illuminates the significance of applying artificial empathy and affective computing to AI technology and the effects on the consumer journey. I find supportive evidence that high levels of artificial empathy and accurate emotion detection resulted in subjects viewing the AI smart assistant as more likeable and intelligent. High empathetic interaction, compared to low, also increased participants' comfort and perceived support and understanding from the AI smart assistant. This research will help determine the direction of what artificial empathy might serve to impact along the consumer journey. Society has little understanding of how people engage with this technology and the emotional and cognitive impacts on consumer behavior. As AI becomes more implemented into society, it is important to understand how it can positively or negatively affect users' experiences.

# TABLE OF CONTENTS

# CHAPTER 1

# INTRODUCTION

Artificial Intelligence (AI) and chatbots are considered the most important emerging technologies of 2020 (Petrock, 2020). The intersection of these technologies is found in virtual digital assistants often referred to as virtual agents or smart assistants (Petrock, 2019a). In consumers' homes, the most conspicuous and popular applications of smart assistants include Apple's Siri, Google Assistant, Amazon Alexa or Microsoft's Cortana (Petrock, 2019a) where consumers can request audio content, ask questions and make purchases (Perrin, 2020). According to eMarketer, an estimated 111.8 million people in the United States (US) regularly used an AI voice assistant in 2019, representing approximately a 40% increase in the number of individuals engaging with such technology over a three-year time period (Petrock, 2019b). The number of people using smart assistants worldwide is projected to reach 1.8 billion by 2021 (GO-Gulf, 2018) and by 2022 it is estimated that more than half of US households will own and operate at least one voice-enabled smart speaker (Perez, 2017). US and United Kingdom (UK) consumers are already spending \$2 billion per year shopping via smart speakers (Perez, 2018). In response to this increase in consumer adoption, smart speaker marketing expenditures are expected to grow to \$19 billion globally by 2022 (Perez, 2018).

AI refers to machine or computer processes that portray intelligence by simulating human-like behavior (McCarthy et al., 2006). As the availability of data grows and algorithms become more robust, such simulation of human behavior will more closely replicate actual human interaction (Petrock, 2019a). For instance, smart assistant chatbots have emerged - which utilize speech- or text-based conversation to interact with users through complex AI processes such as Natural Language Processing (NLP) as well as organize, store and output information based on the users' specific data (Petrock, 2019a).

As AI technology advances and is more robustly integrated into smart assistants, such technology will become more intertwined into consumers' personal lives and may play an increasing role in shaping consumer experience (Petrock, 2020).Through integration in consumers' home systems, appliances and other devices, smart assistants will acquire a better understanding of the consumers' needs than brands themself due to the excess of data collected. This shift will likely cause brands to invest in AI platform optimization as opposed to direct relationships with consumers (Dawar, 2018).

In this project I will adopt the term AI smart assistant to refer to smart assistants with AI technology embedded that serves to direct interactions with consumers. I will pull from various literature on human-computer interaction (HCI), embodied agents, conversational agents, computers, voice assistants and intelligent systems to explore the role AI smart assistants may play in consumer behavior. The empirical focus will be on AI smart assistant technology that can respond to consumers' comments, voice, questions, requests, actions, or emotional state in real-time and then engage with the consumer regarding subsequent action.

Marketing that leverages such AI smart assistants to create personalized consumer experiences may be critical going forward given 51% of Gen X and 67% of Millennials/Gen Z populations expect offers from companies to always be personalized (Salesforce, 2018). However, such investment does not come without risk, 60% of consumers are concerned about their personal information being compromised because of AI (Salesforce, 2018). Seventy-three percent of US internet users think it is important for companies to protect their data privacy, though only 25% trust them to actually do it (Petrock, 2020). In fact, the benefits of personalization in email communication and advertising are capped. When too much personalization is present, consumers' concerns regarding privacy and data collection can outweigh the benefits of highly targeted information (Aguirre et al., 2016; White et al., 2008).

Chellappa and Sin (2005) were among the first to explore this trade-off between personalization and privacy in an online context which later became known as the personalization-privacy paradox (Awad & Krishnan, 2006). In general, personalized online services are less impacted by this paradox than personalized advertisements (Awad & Krishnan, 2006; Chellappa & Sin, 2005). It seems that managing consumers' sense of vulnerability by being overt and making the consumer feel special is important (Aguirre et al., 2016). Social and intimate communication has also shown to be effective in breaking down the personalization-privacy paradox (Song et al., 2014). This suggests a potential marketing role for AI smart assistants in the development and maintenance of relationships with consumers. Given “consumers’ allegiance will shift from trusted brands to a trusted AI assistant" (Dawar, 2018, pg. 11), these assistants may become an influencer in consumer behavior. However, establishing a genuine connection between the consumer and an AI smart assistant or fostering reliance on an AI smart assistant by a consumer may require specific types of interaction. In particular, empathetic social interaction facilitated by emotion detection, may be what is needed to grow trust between the technology and humans (Moore, 2018).

AI smart assistants will become more in tune with contextual scenarios of consumers and their emotional responses by utilizing sensors in the mechanism itself or other connected devices, resulting in these devices having the potential to detect users’ emotions and to adopt the appearance of empathy (Picard et al., 2001; Picard & Klein 2002). As AI smart assistants increasingly engage in emotion detection and response, often referred to as affective computing, consumers may feel more responsive to the smart assistant. Previous research has shown that when consumers interact with computers that disclose intimate emotions (Moon, 2000) or express emotion regarding a consumer’s positive or negative outcomes (Brave et al., 2005), consumers perceive the computer more favorably on a social level. When a computer agent expressed appropriate emotion in an empathetic response to a consumer’s wins or losses in a game, the computer was perceived as more caring, likable, trustworthy and supportive (Brave et al., 2005). If a consumer perceived a computer as more attractive (likable, friendly, kind and helpful), the consumer was more interested in making product purchases while using that same device (Moon, 2000). In this work I explore whether an AI smart assistant that engages in an empathetic interaction can engender similar positive perceptions from a consumer but also enhance a consumer’s openness to recommendations or ideas shared by that AI smart assistant.

## Problem Significance

To break through the personalization-privacy paradox and provide consumers with the experience they desire, businesses must resolve the paradox and explore how AI smart assistant interaction may be beneficial or problematic for consumers. The benefit of this study is determining how increasingly popular AI smart assistant technology may impact consumers' perceptions and openness to recommendations from that assistant. People are exposed to experiences regarding this technology every day. This capability is available via many outlets such as smartphones, laptops, speakers, televisions and even some household appliances – devices that society is consistently reliant on. However, there is little data about how users are responding to this technology. By conducting this research, I will be able to learn how people feel about AI smart assistants and how they respond to interactions with an AI smart assistant. More generally, this research is beneficial in its contribution to knowledge regarding the effects of technology on consumers. Sixty-nine percent of households in the US own an AI smart assistant (Petrock, 2019d). However, society has little understanding of how people engage with these devices and the overall emotional and cognitive impacts on consumers. As this technology becomes implemented even more into society's everyday activities, it is important to understand how it can positively or negatively affect users' experiences and behaviors.

## Hypotheses

1. AI smart assistants demonstrating higher levels of artificial empathy vs. lower will result in consumers being more open to recommendations from the smart assistant.
2. AI smart assistants accurately identifying consumers' emotions vs. inaccurately will result in consumers being more open to recommendations from the smart assistant.
3. AI smart assistants demonstrating higher levels of artificial empathy vs. lower will be perceived as more likable and trustworthy.
4. AI smart assistants demonstrating higher levels of artificial empathy vs. lower will be perceived as more intelligent.
5. AI smart assistants demonstrating higher levels of artificial empathy vs. lower will be perceived as more supportive.
6. AI smart assistants demonstrating higher levels of artificial empathy vs. lower will create a stronger sense of comfort and ease in consumers.

7. AI smart assistants demonstrating higher levels of artificial empathy vs. lower will be perceived as having greater understanding and perspective-taking.

## DEFINITION OF TERMS

*Affective Computing:* The study and development of systems and devices that can recognize, interpret, process, and simulate human affects. It is an interdisciplinary field spanning computer science, psychology, and cognitive science.

*Artificial Intelligence:* The capability of a machine to imitate intelligent human behavior.

*Biometrics:* The technical term for body measurements and calculations. It refers to metrics related to human characteristics. Biometrics authentication is used in computer science as a form of identification and access control.

*Computer:* Machine that can be instructed to carry out sequences of arithmetic or logical operations automatically via computer programming.

*Conversational Agent:* Computer system intended to converse with a human.

*Embodied Agent:* Intelligent agent that interacts with the environment through a physical body within that environment.

*Empathy:* The ability to form an embodied representation of another's emotional state, while at the same time being aware of the causal mechanism that induced the emotional state in the other.

*Gen X:* The demographic cohort typically born years around 1965 to 1980.

*Gen Z:* The demographic cohort typically born years around 1996 to 2010.

*Human-Computer Interaction:* Studies the design and use of computer technology, focused on the interfaces between people and computers.

*Intelligent System:* Technologically advanced machines that perceive and respond to the world around them.

*Mimicry:* The imitation of the emotional expressions of others.

*Millennials:* The demographic cohort typically born years around 1981 to 1996.

*Smart Assistant:* Software program (sometimes called an intelligent virtual agent (IVA), virtual rep or chatbot) that uses scripted rules and, increasingly, artificial intelligence applications to provide automated service or guidance to humans.

*Smart Device:* Electronic device, generally connected to other devices or networks via different wireless protocols.

*Voice Assistant:* Digital assistant that uses voice recognition, speech synthesis, and natural language processing (NLP) to provide a service through a particular application.

# CHAPTER 2

# LITERATURE REVIEW

## IMPORTANT EVENTS IN AI EVOLUTION

While the term Artificial Intelligence (AI) has recently emerged as a topical technological force, it was over 60 years ago that John McCarthy and Marvin Minsky coined the term explaining AI as "the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it" (McCarthy et. al. 2006, p.12). There is now an umbrella of ideas under the concept of AI which include narrow intelligence and general intelligence. Narrow intelligence refers to the ability to accomplish a narrow set of goals such as playing chess or driving a car (Goertzel, 2014). General intelligence, also referred to as human level AI or broad intelligence, is the ability to accomplish any goal, including learning, at least as well as any human (Goertzel, 2014).

Groundbreaking forms of narrow intelligence emerged at the turn of the last century. In 1997 IBM's Deep Blue was the first computerized chess-playing program to beat a world-reigning human champion under standard chess tournament time controls – developed with the ability of memorization and computation, but no active learning (Tegmark, 2017). Then in 2011 IBM released another narrow AI marvel, Watson. Watson was a natural language question answering computer which competed on Jeopardy and defeated two former champions – developed with custom programmed skills, memorization and speed (Tegmark, 2017).

In 2015 Google joined in on the action when their computer programming company, Deepmind, released an AI system that was able to master multiple computer games without any instruction. This outcome was particularly ground-breaking because it introduced a new component to narrow intelligence – deep learning by a set of neural networks (Tegmark, 2017). In 2016, Deepmind developed AlphaGo based on deep neural networks allowing this system to develop an understanding of reasonable human play of the popular Chinese game, Go. Through the power of reinforcement learning, AlphaGo went on to defeat the Go world champion (Tegmark, 2017). It is the development of deep learning networks that some may consider as the first step in AI moving away from narrow intelligence to more of a sliding scale between narrow and general capability.

AI's advancements of deep learning neural networks have simultaneously advanced human-computer interaction. The innovative development of Natural Language Processing (NLP), ability for computers to interact with people using spoken language, and Natural Language Understanding (NLU), the ability of computers to recognize text or speech sentences, has dramatically advanced a machine's processes as indistinguishable from human intelligence (Ammerman, 2019). Most recently, IBM released a new AI system that mastered the art of persuasion and human language – Project Debater. With the help of neural networks, IBM was able to train the AI model in three areas; listening comprehension, modeling human dilemmas, and data-driven speech writing and delivery (Teich, 2019a). This type of technology is the first of its kind to debate humans on complex topics using persuasive arguments. The combination of NLP that Project Debater leverages along with its ability to make well-informed decisions, has led many to actually anthropomorphize the AI machine as though they were engaging with a human social actor (Teich, 2019b). However, due to Project debater's lack of empathy, it has been considered by some to have entered into the uncanny valley, where anthropomorphization becomes unfavorable for the human listener or reader (Teich, 2019b). In order for AI to advance into more general conversational intelligence, it will need to adopt the ability to empathize with users, which Picard (1997; et al., 2001) states can be achieved through affective computing.

## AFFECTIVE COMPUTING: EMOTION DETECTION AND AFFECT PERCEPTION

Affective computing, refers to a machine's ability to recognize, interpret, process and simulate human emotions (Picard, 1997) with the goal of "adapting computational systems to these states" (Picard, 1997, p. 24). Word choice and perception-based factors such as facial expression, voice tone, and hand or body movements are the most common emotion detection metrics used to measure affect perception and likely to be the launch point for future affective computing technology (Accenture, 2020). However, research has revealed that other physiological metrics may have a more accurate level of detection (Cernea & Kerren, 2015). Skin conductance, for example, is a sympathetic nervous system response that can be measured to help detect emotion through electrodermal activity (EDA) (Poh et al., 2010). Rosalind Picard expresses this technology can be more accurate than electroencephalographic (EEG) readings (L. Fridman, personal communication, June 17, 2019). EEG readings alone have recorded emotion recognition rates up to 90% accuracy (Sourina & Liu, 2014). Additionally, Picard has stated that detecting physiological factors from a wearable device is greater than 80% effective at forecasting affect (L. Fridman, personal communication, June 17, 2019). Beyond wearables, physiological metrics such as Heart rate (HR), respiratory rate, and HR variability (HRV, an index for cardiac autonomic activity) are now able to be detected through video or webcam footage (Poh et al., 2011) creating great flexibility in how affect may be detected. Furthermore, when a variety of these metrics are analyzed in combination, accuracy of affect recognition is likely to increase (L. Fridman, personal communication, June 17, 2019; Picard et al., 2001). Affect detection via biometrics is further enhanced by access to information regarding the user's context, situation, goals, and preferences (L. Fridman, personal communication, June 17, 2019; Picard et al., 2001).

Emotion detection could positively impact human-computer interaction by providing users with new support tools; experiential emotional aids, emotional skill-building and pre-emptive tools (Picard & Klein, 2002). Emotional skill building for the user could result when AI technology provided feedback to the user regarding a strong emotional state that was detected. In addition to aiding in the identification of emotion, this could increase users' self-awareness and support emotion management (Picard & Klein, 2002). Recognizing and differentiating the presence of a specific emotion enhances how one regulates and responds to those emotions (affective influence regulation), which leads to making better decisions (Seo & Barrett, 2007).

Emotion detection as a pre-emptive tool could be utilized to shape the human-computer interaction. This type of system would be able to predict user affect and would use this detection to help maintain a user's positive affective state or to avert a negative emotional response (Picard & Klein, 2002). For example, predicting when a user may become frustrated can help guide an intelligent system when to intervene with support or, on the contrary, to allow a user to continue to be uninterrupted if they are not needing any support (Kapoor et al., 2007). When support is needed, experiential emotional aids could leverage empathy (Klein at el., 2002; Picard & Klein, 2002). As a result of empathetic communication, computers may serve to mitigate negative emotions among users (Klein et al., 2002; Picard & Klein, 2002) and support positive outcomes. Recommendations offered by empathetic AI agents to support users' personal struggles has been shown to enhance users' mental well-being (Inkster et al., 2018).

However, the accuracy of affective computing is subject to human inference, since emotion meaning must still be derived from physiological measures (Barrett et al., 2019). As an example, Picard et al. (2001) identified that physiological measures for different emotions from the same day tended to be more similar than when measuring the same emotions on different days, which makes interpretation reliant on perceiver-dependent measurements. Therefore, these emotion detection metrics are sometimes unreliable and should be utilized with caution. That being said, research suggests that people apply the social rules of human-human interaction to human-computer interaction (Nass & Moon, 2000). Given humans do not always accurately recognize others' emotions, it is possible a user would not be entirely impacted by a machine's incorrect emotion detection (Picard, 2003). Scheirer et al. (2002) argue that emotions of users will not always be explicit, despite the accuracy of detection methods, and therefore many times users will likely need to be prompted for detailed feedback.

## ARTIFICIAL EMPATHY

The presence of affective computing in human-computer interaction has created the opportunity for computers to adopt more human-like skills such as empathy (Picard & Klein, 2002). Empathy has been defined in a variety of ways. For example, there are two subsets of empathy: cognitive and emotional (Hodges & Myers, 2007). Both forms of empathy may be modeled in an artificial manner but rely on different processes. Emotional empathy pertains to a non-conscious response where an individual mimics the emotional state of another through an embodied representation (Asada, 2014). An embodied representation is triggered by emotional contagion, which is closely related to motor mimicry and directly linked with emotional empathy (Asada, 2015). To create artificial emotional empathy, an agent synchronizes with the emotion of an individual experiencing an affective state, causing the agent to exemplify a similar emotional output (Asada 2015). Cognitive empathy involves perspective-taking and is paired with a cognitive understanding of what others are feeling (Ickes, 1993).

However, according to Picard and Klein (2002), it is not enough to implement a human-like trait if it is implemented poorly. Therefore, in order to enhance artificial empathy to an appropriate human-like level, AI smart assistants should consider adopting sympathetic concern and perspective-taking, in addition to emotional contagion, to successfully achieve implementing empathy into a human-computer interaction (de Waal, 2008; Gonzalez-Liencres et al., 2013). Artificial emotional and cognitive empathy may both be activated by intertwining direct emotion measurement with contextual factors, such as current mood states and other environmental contingencies (Gonzalez-Liencres et al., 2013). In human-to-human interaction empathy is not simply a function of expressing identical emotions to another but is informed by appraisal processes about what is causing another's emotional state (Wondra & Ellsworth, 2015). Thus, an empathic reaction does not always need to be precisely the same emotion as observed in another, but a relevant emotional response needs to be present in order to imitate empathy. Therefore, I will leverage the definition of artificial empathy from Tapus et al. (2007):

> In order to emulate empathy, an [AI] system should be capable of recognizing the user's emotional state, communicating with people, displaying emotion, and conveying the ability of taking perspective. It should appear as if it understands others' emotions, can mimic those emotions, and can behave as if the others' emotions affect it. (para. 20)

I will define an empathetic interaction from an AI smart assistant as a stated recognition of the consumer's emotional state, communication with relevant emotional response and behavior as if the other's emotions affect it, and conveyance of perspective-taking relevant to the emotional state.

## EFFECTS OF DEMONSTRATED ARTIFICIAL EMPATHY

AI is already able to develop useful solutions by evaluating the data resulting from users' interconnectivity of devices and platforms. However, in order to convey these solutions to users successfully, it is hypothesized that the communication needs to connect with the user on a positive social level (Song et al., 2014). When consumers interact with an anthropomorphized device, they are likely to treat the device according to their own social beliefs and norms towards humans (Kim & McGill, 2018). The more a machine behaves according to socially appropriate norms, the more successful the machine is at eliciting intimate information from the user (or consumer) (Moon, 2000). Users who perceive a device to be more similar to their behavior style (e.g., dominant or submissive), were more open to influence from the device, thought the information from the device was of higher quality, found the device friendlier, and conformed more to the device's influence (Nass et al., 1996; Nass & Moon, 2000). It has also been concluded from studies that people establish a social presence with and develop attraction to technology when the machine shares similarities with the human user, such as matching the users' personality (e.g., introversion or extroversion) (Lee & Nass, 2005).

It has also been proven that adding NLP and social role fulfillment, such as helping the user, to a computer's personality will help increase perceived intelligence and encourage acceptance of the technology (Dryer, 1999). The Computers as Social Actors Paradigm (CASA) presented by Nass and Moon (2000) provides further insight into understanding human-computer interaction and how the usage of human-like cues has significant influence on emotional connection. These findings provide initial evidence that conversational agents, when using human-like cues, can have a positive effect on relationship building (Araujo, 2018).

Building empathy specifically into AI may grow trust between the technology and humans (Moore, 2018). According to Picard et al. (2001), computers with emotional skills, such as the ability to recognize emotion of a user or express emotion, will likely be perceived as more intelligent due to the idea that this interaction is a form of emotional intelligence. While emotional intelligence was not directly measured against perceived intelligence of the computer, the presence of emotional intelligence did cause an increase in perceived sense of trust and care of the device (Picard, 2004).

In exploring emotion exhibited by embodied computer agents, Brave et al. (2005) investigated how participants reacted toward embodied computer agents that expressed positive response to their win in an online game of blackjack or negative response to their loss in the game via text message speech bubbles. Such an interaction increased perceptions that the agent was caring, likeable, and trustworthy. The agent was also perceived to be more supportive. This research provides suggestive evidence that empathetic interaction can engender positive perceptions of computer agents.

Leite et al. (2013) tested the influence of empathy in human-robot interactions. They concluded that users are actually able to decipher empathetic behaviors conveyed verbally by a robot, and this therefore creates a more positive perception of the machine for the user. Empathetic behaviors performed by the robot led users to consider the machine as more encouraging and sensible (Leite et al., 2013). In fact, in an experiment with GPS system navigation, it was concluded that the tone of the navigation system's voice, whether happy or sad, directly impacted the emotional state of the driver and that people drove much better when the tone of the navigation system matched their own emotional state (Takayama & Nass, 2008).

Despite evidence that artificial empathy has positive impacts on consumers' perceptions of technology. It may be argued that AI smart assistants conveying a sense of empathy could be considered inauthentic, resulting in less trust from the user (Picard & Klein, 2002). Users may detect that, although a computer is identifying a particular emotion and demonstrating human-like behavior, there is still a lack of understanding of their problem (Picard & Klein, 2002). However, Picard and Klein (2002) explain that, despite the risk of appearing inauthentic, artificial empathy has a high likelihood of resulting in a positive interaction. They note that even human-human empathetic interactions are sometimes inauthentic and if a person's specific emotional needs are met by a machine there is a human tendency to anthropomorphize that object.

Reeves and Nass (1996) coined the term, Media Equation, around the notion that their research suggested people displayed a natural predisposition to treat machines as if they were people. According to Google, in 2018 41% of people who owned a voice-activated speaker said it felt as if they were talking to a friend or another person (Kleinberg, 2018). Consumers have even considered online recommendation systems as social actors, perceiving characteristics such as integrity and benevolence within the technology (Wang & Benbasat, 2005). Anthropomorphized messengers have also been shown to influence and persuade consumers more so than human salespersons (Touré-Tillery & McGill, 2015).

Moon (2000) determined that a user who perceived a computer as more attractive (likable, friendly, kind and helpful) was also more accepting of product offerings viewed through that device. Users assigned these positive characteristics to the computer after participating in an intimate human-computer interaction, where each entity performed intimate emotional self-disclosures through text-based communication. After which, users were assigned either the same or a new computer for an interactive shopping experience. Users' behaviors depicted that the bond developed with the computer during intimate self-disclosure directly impacted interest in products.

## THEORETICAL SIGNIFICANCE

If artificial empathy is able to be successfully demonstrated among AI smart assistants, it is expected that it would directly impact user perceptions of the device and potentially may cause users to be more open to recommendations offered by the assistant. Brave et al. (2005) determined users will perceive an empathetic computer as more caring, likable and trustworthy, as well as more supportive. However, they did not explore a more directive specific empathetic interaction. I postulate that empathetic interactions will generate similar responses and, subsequently, the more empathetic the interaction the higher the perceptions of care, likeability and trustworthiness will be. Since Picard et al. (2001) equate emotion detection to emotional intelligence, I further predict that if accurate emotion detection is present the AI smart assistant will be perceived as more intelligent, which may be positively impacted by a highly empathetic interaction. While Moon (2000) did not fully implement empathy into the human-computer interactions, consumers shared many similar positive perceptions as in Brave et al. (2005). Therefore, given Moon's (2000) findings that positive perceptions of a computer regarding attractiveness (likeability, friendliness, kindness and helpfulness) resulted in individuals being more open to product recommendations presented by that computer system, I predict that increased positive perceptions from empathetic interactions with an AI smart assistant will result in increased openness to recommendations from the device. I explore whether this is a more general receptivity versus willingness to adopt very specific recommendations. This experimental study will test the assumption that the more empathy an AI smart assistant portrays, the more positively the subject will respond to a recommendation from that assistant.

# CHAPTER 3

# RESEARCH QUESTIONS AND HYPOTHESES

## Hypothesis 1

Will consumers interacting with an AI smart assistant demonstrating a high level of artificial empathy be more inclined to consider recommendations from the assistant? Consumers increasingly feel as if they are talking to a friend or another person when using their AI voice assistant (Kleinberg, 2018) and such anthropomorphized technology has also been shown to be highly persuasive to consumers in contrast to human salespersons (Touré-Tillery & McGill, 2015). Moon (2000) determined that a user who perceived a computer as more attractive (likable, friendly, kind and helpful) was also more accepting of product offerings viewed through that device. Thus, I predict that consumers who experience a strong empathetic interaction from an AI smart assistant versus a weak empathetic interaction will be more open to receiving recommendations from that smart assistant. Hypothesis 1: AI smart assistants demonstrating higher levels of artificial empathy vs. lower will result in consumers being more open to recommendations from the smart assistant.

## Hypothesis 2

Will consumers interacting with an AI smart assistant demonstrating accurate emotion detection versus inaccurate emotion detection be more inclined to consider recommendations from the assistant? I predict that when AI smart assistants accurately detect (versus inaccurately detect) an emotion, the consumer will be more willing to have the AI share recommendations despite the level of artificial empathy. Therefore, it is suggested that the moderate empathetic interaction condition (versus low empathetic interaction) and the high empathetic interaction condition (versus confused empathetic interaction) will result in consumers' being more open to receiving recommendations. Hypothesis 2: AI smart assistants accurately identifying consumers' emotions vs. inaccurately will result in consumers being more open to recommendations from the smart assistant.

## Hypothesis 3

Will consumers interacting with an AI smart assistant demonstrating a high level of artificial empathy have a more positive social perception of the AI smart assistant? Past research has concluded that a computer that displays an emotional response consistent with a users' outcome has resulted in subjects viewing the embodied computer agent as more likeable and trustworthy (Brave et al., 2005). I predict that AI smart assistants displaying high versus low artificial empathy will result in more positive social perceptions of the AI smart assistant. Hypothesis 3: AI smart assistants demonstrating higher levels of artificial empathy vs. lower will be perceived as more likable and trustworthy.

## Hypothesis 4

Will consumers interacting with an AI smart assistant demonstrating a high level of artificial empathy result in greater perceptions of emotional intelligence? Asada (2014) demonstrates that technology that is able to detect a user's emotion and then reflect that emotion has the ability to demonstrate perceived empathy. More specifically, if the technology is able to recognize and mimic traits of the same emotion as the user, this can be observed as emotional contagion which directly correlates to emotional empathy. Picard et al. (2001) suggests that the presence of emotion detection correlates with emotional intelligence and the AI smart assistant will be perceived as more intelligent compared to when there is little to no emotion detection involved. I predict that AI smart assistants displaying high versus low artificial empathy will be perceived as more intelligent by consumers. Hypothesis 4: AI smart assistants demonstrating higher levels of artificial empathy vs. lower will be perceived as more intelligent.

## Hypothesis 5 and 6

Will AI smart assistants demonstrating high empathetic interactions (versus low) cause subjects to feel supported and feel more at ease? According to Gonzalez-Liencres et al. (2013) and de Waal (2008) support stems from an aspect of empathetic concern often referred to as compassion. Hence, I assume if the smart assistant is reflecting high empathetic concern for the subject, then it will be perceived as more supportive resulting in a stronger sense of comfort and ease in consumers. Hypothesis 5: AI smart assistants demonstrating higher levels of artificial empathy vs. lower will be perceived as more supportive. Hypothesis 6: AI smart assistants demonstrating higher levels of artificial empathy vs. lower will create a stronger sense of comfort and ease in consumers.

## Hypothesis 7

Will smart assistants demonstrating high empathetic interactions (versus low) be perceived as more understanding of the consumer's perspective? Perspective-taking is an extremely important component to empathy (de Waal, 2008; Gonzalez-Liencres et al., 2013; Yamamoto, 2016). Perspective-taking strongly emphasizes the concept of understanding another's point of view. I assume that if a smart assistant is participating in high empathetic interactions, then it is likely that subjects will perceive the smart assistant as understanding their perspective. Hypothesis 7: AI smart assistants demonstrating higher levels of artificial empathy vs. lower will be perceived as having greater understanding and perspective-taking.

# CHAPTER 4

# METHODOLOGY

AI smart assistants are intertwining themselves into people's everyday lives and research has begun to try to explore how to develop artificial empathy into such technology (Asada, 2015). However, there is scant research on people's reaction to this type of technology, especially when it is perceived as responsive to users' emotions. Further, there is little to no research regarding how consumers will respond to empathic interactions with such devices. Such interactions may affect people's perceptions of the technology, perceived sense of support and comfort from the technology, as well as impact their openness to ideas or recommendations shared by such technology. Brave et al. (2005) showed that emotive expression relevant to a users' outcomes, increased users' perceptions of care, likability, trust and support. There has been minimal research to investigate how today's technology can actually influence consumers if such technology adopts empathetic behavioral interactions toward the consumer. As society shifts to performing more tasks online, especially regarding online learning and remote working, it's important to understand the effects that smart assistants can have on user's perceptions and experiences.

This research was initiated on the basis of consumer research, a subset of marketing research, to determine how consumers will perceive AI smart assistants that are able to tap into biometric indicators, with the help of wearable devices and even cell phones, to determine emotion and then empathize with that emotion. An online platform was used to administer a series of statements and questions depicting a simulated conversation between subjects (the potential consumer) and the AI smart assistant. The platform was a survey tool and embedded questions were utilized to measure subjects' perception of the AI. Since this research is considered quantitative market research, several statistical analysis techniques were used to process the response data in order to derive meaning and develop clear insights into consumers' perception of and their openness to recommendations from the AI smart assistant.

## Research Design

The development of artificial empathy can be framed in terms of the argument that empathy in humans involves emotional contagion, sympathetic concern, and perspective-taking (de Waal, 2008; Gonzalez-Liencres et al., 2013). So, this work sought to create context to examine consumer reactions to a set of interactions with an AI smart assistant that included these elements; where the AI smart assistant expressed its experience of a common emotion, showed sympathy, and communicated perspective-taking. To create an experience of observed emotional contagion by the AI smart assistant in a textual context, I utilized two tools; interjections (i.e., ugh, argh) and emotion words (i.e., irritating, annoying). Interjections hold the ability to indicate basic emotions (Goddard, 2014). Interjections can be used to express how one feels something or knows something (Wierzbicka, 2003), which is what the AI smart assistant simulation is attempting to convey to the individual with whom it is interacting. Additionally, it has been proven that emotion words invoke a stronger sense of a person's emotion, more than facial expression (Altarriba et al., 1999; Gendron et al., 2012). Therefore, the AI smart assistant dialogue included interjections and emotion words into the AI smart assistant's text responses that state the emotion or emotion concepts and associations. In addition, the dialogue incorporated statements regarding aspects of sympathy, care and support as well as perspective-taking and understanding (de Waal, 2008; Gonzalez-Liencres et al., 2013).

The research study employed a quasi-experimental nonequivalent groups between-subjects design. The study involved three different tasks during an online research session that subjects participated in for extra credit in a course. The first task aimed to induce incidental emotions that, in the real world, usually carry over from a user's consumption of media. To do this, participants were exposed to an article based on current worldly issues, in order to evoke a result similar to a real-life scenario where emotion around current events would possibly carry over to their future interaction with an AI smart assistant. This article highlighted the new requirements and challenges of remote working and schooling during the Covid-19 pandemic of 2020. This content focused on the sense of stress and anxiety of

Covid-19 toward the potentially frustrating challenges of current circumstances. Afterwards subjects were presented a second very short, unrelated task, that asked questions about interior design to create a disconnect between the emotion priming article and the main portion of the research study. The third task introduced subjects to a simulated AI smart assistant, referred to as a virtual schoolmate, that appeared to be designed to assist students with tasks associated with school. When discussing the subjects' current circumstances, the AI smart assistant (virtual schoolmate) either engaged in a strong empathetic interaction or weak empathetic interaction with an individual, where the empathetic engagement began with the smart assistant dialoguing with the participant and asking what was on their mind relative to school. For all participants the AI smart assistant ended up indicating it was detecting frustration in the respondent. The AI smart assistant then either expressed emotional contagion and a desire to understand or no understanding of how it feels to be in a state of frustration. Then the AI offered perspective-taking of frustration specifically with responses showing awareness of the causal mechanism that might have induced an emotional state of frustration (Gonzalez-Liencresa et al., 2013). Given the experience of frustration was the only emotion that matched the preset interaction with the AI smart assistant, this ultimately allowed the separation of participants into four groups (See Appendix A):

- Group 1 High Empathetic Interaction Condition-AI emotion detection accurate [high frustration state and AI identifies frustration], emotion synchronization and similar emotion output present [frustrated emotion concepts expressed by AI], high level of perspective-taking [I know how that feels and offered examples of what can be frustrating] and understanding [explicitly conveyed it wanted to understand and support the respondent]
- Group 2 Moderate Empathetic Interaction Condition-AI emotion detection accurate [high frustration state and AI identifies frustration], emotion synchronization and similar emotion output absent [confused emotion concepts expressed by AI], moderate level of perspective-taking [I do not know how that feels but offered examples of what can be frustrating] and understanding [did not state it explicitly wanted to understand or support the respondent]
- Group 3 Confused Empathetic Interaction Condition-AI emotion detection inaccurate [low frustration state and AI identifies frustration], emotion synchronization and similar emotion output absent [frustrated emotion concepts expressed by AI], high level of perspective-taking [I know how that feels and offered examples of what can be frustrating] and understanding [explicitly conveyed it wanted to understand and support the respondent]

- Group 4 Low Empathetic Interaction Condition-AI emotion detection inaccurate [low frustration and AI identifies frustration], emotion synchronization and similar emotion output absent [confused emotion concepts expressed by AI], moderate level of perspective-taking [I do not know how that feels but offered examples of what can be frustrating] and understanding [did not state it explicitly wanted to understand or support the respondent]

## RESEARCH METHODOLOGY

At the beginning of the session participants were told that they would be participating in three separate research studies during the current session and that they should take their time to answer the different questions in each study carefully.

### Research Study 1

The first task began with a screen that presented a unique graphic and stated it was "Study 1" (See Appendix B Figure B1). The next screen indicated that researchers were "interested in how the formatting of an online news article can affect your memory for certain information and facts." Then it asked participants to "please carefully read the article snippet on the next page and answer the questions that follow." Participants were presented with an article that discussed the challenges to productivity in work and school due to the Covid-19 pandemic. The article highlighted how adjusting to virtual learning, socializing remotely, being asked to learn new skills, and the necessity of finding work-life balance might negatively affect an individual's success. The article was intended to highlight some of the stresses due to Covid-19 and the expectation was that if the individual attributed the sense of stress as outside their personal control, that would manifest in some level of frustration. Participants were then asked a series of questions to match the guise of the task being about testing memory and asked if the subjects could "recall a reason from that article that causes people to struggle with work-life balance" and "how many people are working from home or doing virtual learning in the United States."

### Research Study 2

In a second task, intended to create a disconnect between the article priming subjects to focus on external stressors in the first part of the research session and the core research questions, participants saw a screen that stated, "Study 2 Design Style Study" (See Appendix

B Figure B2). The graphic in the mock Study 2 was an entirely different set of colors and text style. In the graphic it stated that "we are collecting information on design style preferences." Participants were shown five interior design styles and asked which one they prefer. This was followed up with a question about how they categorized their interior design preferences.

## Research Study 3

Finally, participants were presented with yet another graphic that stated, "Study 3" and welcomed subjects to "engage with the newest smart technology for students" and record their opinions (See Appendix B Figure B3). During this section of the research, subjects participated in a simulated AI conversation. This was part of an interactive survey simulating a conversation with the AI smart assistant, where it introduced itself as a "virtual schoolmate," and asked if the participant was a college student. If the subject stated yes, the AI smart assistant asked where they attended school and welcomed them as a student of that institution by name of the institution's mascot. Next, the assistant indicated it was a "cloud-based AI college assistant" and explained how it can "help you with lots of things like managing your schedule, providing reminders and sharing ideas on how to be successful in your studies." The conversation went on to ask participants what was on their mind with school and then randomly assigned them to one of two conditions: (1) a strong empathetic interaction with an AI smart assistant where the AI engaged empathetically by prompting subjects to "please write a couple sentences so I can really understand what you're experiencing," or (2) a weak empathetic interaction where the AI engaged by only asking, "please write a couple sentences."

Thereafter, the AI smart assistant indicated the emotional state it detected in respondents, but the emotion detection was only designed to indicate that it detected feelings of frustration by stating, "It sounds like you're a bit frustrated," and then confirmed whether this was true by having subjects specify whether they were "not frustrated at all," "not really frustrated," "not sure whether they were frustrated or not," "kind of frustrated" or "so frustrated" (assigned values 1-5 respectively). Based on these values, only subjects who indicated they were experiencing the negative externally focused emotion of frustration (> 3) or were not experiencing it (< 3) were retained in the analysis. No participants who indicated "Not sure whether I am frustrated or not" (=3) were retained in the analysis. This allowed for the creation of four groups: (1) those experiencing frustration in the strong empathetic condition which is referred to as the high empathetic interaction condition, (2) those experiencing frustration in the weak empathetic condition which is referred to as the moderate empathetic interaction condition, (3) those who were not experiencing frustration in the strong empathetic condition which is referred to as the confused empathetic interaction condition, and (4) those who were not experiencing frustration in the weak empathetic condition which is referred to as the low empathetic interaction condition.

The high and confused empathetic interactions attempted to implement emotion synchronization by indicating, “Ugh, how annoying! It upsets me to know that is happening to you.” While the moderate and low empathetic interactions did not implement emotion synchronization and instead indicated, “Hmm, I don't know how that feels.” To enhance empathic responses in the strong empathetic conditions (i.e., high and confused empathetic interactions) the AI smart assistant also incorporated perspective-taking and understanding with phrases such as “I want to better understand the whole picture,” and “I really care about supporting your work as a student.” In the moderate and low empathetic interactions, this element and respective language were absent.

The AI smart assistant then went on to bring up current difficulty with online courses focused on instructors due to ridiculous expectations, overloading students with information and assignments, and making it impossible to keep up. In the next statement, the AI smart assistant stated that online courses can be “confusing with unclear expectations and instructions, and it can be difficult to get questions answered by the professor in a timely manner.” Finally, the AI smart assistant shared “it is also common to encounter technological issues, many times online software does not function properly causing issues beyond the student’s control.” After each of the statements the AI smart assistant asked, “Is this happening to you?” The subjects could then indicate yes or no. Next, the AI smart assistant stated, “What did I miss that has been difficult for you lately? Please tell me more about the frustrations you have been experiencing and what has been most challenging,” and the participant could fill in a response.

In the end, the AI smart assistant either demonstrated strong empathy in an attempt to match emotional output, reflected in the high and confused interactions, by stating, “Argh, I know that can be really irritating!” or weak empathy absent of matched emotional output, reflected in the moderate and low interactions, by stating, “Interesting, I'm not sure how to interpret that.” This portion of the conversation was concluded by asking subjects how long this had been going on.

After learning more about the subject's experience regarding their current academic situation, pertaining to the transfer of all course activities to online platforms, the AI smart assistant indicated it “had some ideas that may be helpful” to the user and asked if they would mind if the device were to share those recommendations. Openness of recommendations was measured using a 5-point scale with endpoints “please don’t” and “please do.” More specific recommendations were then offered such as a deep breathing exercise and the use of a task management app, similar to the virtual schoolmate, with acceptance measured using a 5-point scale with endpoints “extremely unlikely” and “extremely likely.” Subject’s future intent to interact with the AI smart assistant was gauged by if there was interest in having the AI smart assistant email more information about the product or service recommended, measured using a 5-point scale with endpoints “definitely not” and “definitely yes.” These were the key dependent measures of the participants' openness and acceptance toward recommendations offered by the AI.

To conclude the simulated conversation, the AI smart assistant asked subjects to help it gain a better understanding of their feelings so “future recommendations are really on target.” This is where a secondary measure of emotion was implemented to determine how experiencing the device may have changed subjects’ affect. A modified Positive Negative Affect Schedule X (PANAS-X) questionnaire was utilized. PANAS-X was chosen due to its highly consistent validity compared to other mood scales (Watson et al., 1988). Modifications to the scale included adding frustration related emotion concepts, while removing some emotion categories that did not pertain to this study (See Appendix C). This data was used to determine the final emotion of the subject. Then the AI smart assistant thanked the subjects, “for your responses and chatting with me today,” stated “I hope to talk to you again soon...:” and said “Good bye!”

Finally, the AI smart assistant’s interaction was measured on the other dependent variables. To evaluate perception of the AI smart assistant, a set of scales regarding attitudinal measures was used to quantify the subjects’ opinions of the device. This evaluation was added to the very end of the simulated conversation and made to appear separate from the conversation with the AI smart assistant, starting off with, "Thank you for taking the time to interact with our first artificially intelligent virtual schoolmate. Please help us improve [the virtual schoolmate] by answering a few questions." The first set of scales measured perceived character traits of the technology considered in previous research such as, 1) friendly and likeable, 2) trustworthy and sincere, and 3) intelligent and capable, each on a 5-point scale and adopted directly from Brave et al. (2005). Next, this study sought to capture a user's sense of comfort with the AI smart assistant as well as assessments of whether the smart assistant was supportive, understood their situation and engaged in perspective-taking relative to their situation – which are fundamental components to the evolution of empathy (de Waal, 2008; Gonzalez-Liencres et al., 2013; Yamamoto, 2016). In order to measure these perceptions of the AI smart assistant, a modified scale was created by combining portions of the Consultation and Relational Empathy (CARE) measure (Mercer et. al., 2004) and Empathy Questionnaire by Davis (1983). The CARE scale was originally constructed in order to measure a patient's overall perceived empathy of their doctor with the goal in mind to create a consultation process measure. The specific items used from the CARE scale were: (1) "Making you feel at ease," (2) "Letting you tell your 'story,'" (3) "Really listening," (4) "Fully understanding your concerns," and (5) "Show care and compassion" using a 5-point scale. Additionally, key items regarding perspective-taking were modified from the Empathy Questionnaire by Davis (1983) and originally implemented in the EMOTE (2016) project to measure perceived artificial empathy in robot tutors. These specific items were, "Did [the virtual schoolmate]:" (1) "Act supportive," (2) "Consider what it was like to be in your situation," and (3) "Imagine how things look from your perspective" and measured using a 5-point scale.

## Participants

The subject research pool was composed of current students enrolled in a foundation of marketing course at San Diego State University (SDSU). Student subjects participated in an online research setting where they were provided links to virtual Qualtrics surveys.
The primary research pool consisted of San Diego State University students due to their desirable demographic. The Millennial and Gen Z cohort are among the most intertwined with technology as a whole and more likely to utilize biometrics (Petrock, 2019c).

Additionally, there are more than 6 million students in the US (National Center for Education Statistics [NCES], 2017) enrolled in online learning, with that number expected to grow due to the current environment. Therefore, it's important to see how online and digital technologies will affect students' experiences and decisions.

# CHAPTER 5

# RESULTS

## FINDINGS SUMMARY

### H1 Analysis: Openness and Acceptance to Recommendations

Hypothesis 1 suggested that when AI smart assistants engage in a highly empathetic interaction versus low empathetic interaction with a consumer, the consumer will be more willing to have the AI share recommendations. To examine openness of AI smart assistant recommendations a t-test on the item where the AI questioned if it could "share helpful ideas" with the respondent (regarding experiences the respondent found frustrating and challenging lately) (1=Please do not to 5=Please do) indicated no statistically significant difference between the high empathetic interaction condition (M=4.29) versus low empathetic interaction condition (M=3.57); t(12)=.962, p=.364. However, means were directionally consistent with the hypothesis. To further explore consumer acceptance of the AI smart assistant's recommendations, I examined the difference between acceptance of specific activity recommendations such as whether an individual would take advice about a personal health activity, procuring a product, or general ideas from the AI. In the case of sharing the specific helpful ideas of "practicing a deep breathing exercise" (1=Extremely unlikely to 5 =Extremely likely) there was no statistically significant difference between the high empathetic interaction condition (M=3.43) versus low empathetic interaction condition (M=3.2); t(10)=.26, p=.8. In the case of "downloading a time and task management app" (1=Extremely unlikely to 5=Extremely likely) there was also no statistically significant difference between the high empathetic interaction condition (M=3) versus low empathetic interaction condition (M=2.6); t(10)=.493, p=.633. Finally, a t-test on future intent to interact, asking subjects if they would be interested in the AI smart assistant "emailing over more information" about the ideas (1=Definitely not to 5=Definitely yes) once again indicated no statistically significant difference between the high empathetic interaction condition (M=3.29) versus low empathetic interaction condition (M=3); t(10)=.456, p=.658.

## H2 Analysis: Effects of Emotion Detection

Hypothesis 2 suggested that when AI smart assistants detect an accurate emotion, the consumer will be more willing to have the AI share recommendations. Therefore, it is suggested that the moderate empathetic interaction condition (versus low empathy interaction) and high empathetic interaction condition (versus the confused empathetic interaction) will result in consumers' openness to recommendations. To examine consumers' openness to AI smart assistant recommendations, a t-test on the item where the AI questioned if it could "share helpful ideas" with the respondent (regarding experiences the respondent found frustrating and challenging lately) (1=Please do not to 5=Please do) was performed. When analyzing the moderate empathetic interaction (M=3.92) versus low empathetic interaction (M=3.57), there was no indication of a statistically significant difference between the two; t(17)=.458, p=.652. Yet, means were directionally consistent with the hypothesis. However, In the case between the high empathetic interaction condition (M= 4.29) versus confused empathetic interaction condition (M=2.4) there was a statistically significant difference; t(15)=2.84, p=.014.

Hypothesis 2 also suggested that when AI smart assistants detect an accurate emotion, the consumer will be more accepting of specific activity recommendations. When examining acceptance of specific activity recommendations, in the case of sharing the specific helpful ideas of "practicing a deep breathing exercise" (1=Extremely unlikely to 5=Extremely likely) there was a marginal statistically significant difference between the moderate empathetic interaction condition (M=4.3) versus low empathetic interaction condition (M=3.2); t(13)=2.016, p=.065. However, there was not a statistically significant difference between the high empathetic interaction condition (M=3.43) versus confused empathetic interaction condition (M=3.75); t(9)=-.358, p=.729. In the case of "downloading a time and task management app" (1=Extremely unlikely to 5 =Extremely likely) there was no statistically significant difference between the moderate empathetic interaction condition (M=3.7) versus low empathetic condition (M=2.6); t(13)=1.5, p=.157. There was also no statistically significant difference between the high empathetic interaction condition (M=3) versus confused condition (M=2.5); t(9)=.618, p=.552. To determine future intent to interact with the AI smart assistant, a t-test on the item asking subjects if they would be interested in the AI smart assistant "emailing over more information" about the ideas (1=Definitely not to 5=Definitely yes) was performed and indicated no statistically significant difference between the moderate empathetic interaction condition (M=3.1) versus low empathetic interaction condition (M=3); t(13)=.151, p=.882. There was also no statistically significant difference between the high empathetic interaction condition (M=3.29) versus the confused empathetic interaction condition (M=2.75); t(9)=.735, p=.481.

## H3 Analysis: Perceived Likability and Trust

Hypothesis 3 suggested that when AI smart assistants engage in a highly empathetic interaction versus low empathetic interaction with a consumer, consumers will find the AI more likeable. Respondents were questioned about their likability of the AI smart assistant. An index was created for the two items that captured likeability (likeable and friendly) (r=.633). A t-test on likeability (1=Unlikable to 5=Likeable) indicated a statistically significant difference between the high empathetic interaction condition (M=4.79) versus low empathetic condition (M=3.36); t(12)=3.693, p=.003.

Hypothesis 3 also suggested that when AI smart assistants engage in a highly empathetic interaction versus low empathetic interaction with a consumer, consumers will find the AI more trustworthy. Respondents were questioned about their trust of the AI smart assistant. An index was created for the two items that captured trust (trustworthy and sincere) (r=.632). A t-test on trust (1=Untrustworthy to 5=Trustworthy) indicated no statistically significant difference between the high empathetic interaction condition (M=4.07) versus low empathetic condition (M=3.21); t(12)=1.452, p=.172. However, the means were, again, directionally consistent with the hypothesis.

## H4 Analysis: Perceived Intelligence

Hypothesis 4 suggested that when AI smart assistants engage in a highly empathetic interaction versus low empathetic interaction with a consumer, consumers will find the AI more intelligent. Respondents were questioned about their perceived intelligence of the AI smart assistant. An index was created for the two items that captured intelligence (intelligent and capable) ($r=.833$). A t-test on intelligence (1=Unintelligent to 5=Intelligent) indicated a statistically significant difference between the high empathetic interaction condition ($M=4.29$) versus low empathetic condition ($M=2.56$); $t(12)=3.674$, $p=.003$.

## H5 Analysis: Perceived Support

Hypothesis 5 suggested that when AI smart assistants engage in a highly empathetic interaction versus low empathy interaction with a consumer, consumers will perceive the AI as more supportive. An index was created for the two items that captured support (show care and compassion and act supportive) ($r=.768$). A t-test determining if the AI was supportive (1=Strongly disagree to 5 =Strongly agree) indicated a statistically significant difference between the high empathetic interaction condition ($M=4.57$) versus low empathetic condition ($M=3.43$); $t(12)=2.921$, $p=.021$.

## H6 Analysis: Perceived Comfort and Ease

Hypothesis 6 suggested that when AI smart assistants engage in a highly empathetic interaction versus low empathetic interaction with a consumer, consumers will feel more comforted and at ease. A t-test on the AI smart assistant's ability to make the subject "feel at ease" (1=Poor to 5=Excellent) indicated a statistically significant difference between the high empathetic interaction condition ($M=3.14$) versus low empathetic condition ($M=2$); $t(12)=2.489$, $p=.029$.

## H7 Analysis: Perceived Perspective-Taking and Understanding

Hypothesis 7 suggested that when AI smart assistants engage in a highly empathetic interaction versus low empathetic interaction with a consumer, consumers will perceive the AI smart assistant as more understanding. An index was created for the five items that captured perspective-taking (Letting you tell your "story", Really listening, Fully understanding your concerns, Consider what it was like to be in your situation, and Imagine how things look from your perspective) ($\alpha=.92$). A t-test determining if the AI was understanding (1=Strongly disagree or Poor to 5=Strongly agree or Excellent) indicated a statistically significant difference between the high empathetic interaction condition (M=3.37) versus low empathetic condition (M=2.43); t(12)=2.662, p=.021.

## Post Hoc Analysis

To further explore the role of empathetic interaction between an AI smart assistant and a consumer a series of final sets of comparisons were conducted to uncover potential implications for highly empathetic interactions from an AI smart assistant. A t-test indicated that if the AI smart assistant accurately recognized the subject's emotion, there was a statistically significant difference that subjects found it to be more likable in the case of comparing the high empathetic interaction (M=4.79) versus the confused empathetic interaction (M=3.55); t(15)=2.867, p=.015. A t-test also indicated a statistically significant difference that the high empathetic interaction (M=4.29) versus the confused empathetic interaction (M=2.8) was found to be more intelligent; t(15)=3.175, p=.006. There was only a marginal statistically significant difference in likability in the moderate empathetic interaction (M=4.08) versus low empathetic interaction (M=3.36); t(17)=1.728, p=.102. However, there was a statistically significant difference that subjects found the AI smart assistant to be more intelligent in the moderate empathetic interaction (M=3.71) versus low empathetic interaction (M=2.56); t(17)=2.154, p=.046. Therefore, accurately detecting emotion and moderate perspective-taking increased participants' perceived intelligence of the AI smart assistant compared to when the emotion was inaccurately detected.

Furthermore, when comparing high empathetic interaction (M=4.57) to the confused empathetic interaction (M=3.75), both demonstrating strong artificial empathy, it appears that accurately addressing emotion (in the high empathetic interaction) makes a significant difference in perceived support; t(15)=2.564, p=.022. In conclusion, accurate emotion detection increased perceived support.

Demonstrating strong empathy was not successful if the emotion was not accurately detected. A t-test determined it was statistically significant that subjects' openness to recommendations was higher where the AI questioned if it could "share helpful ideas" in the high empathetic interaction (M=4.29) versus confused interaction (M=2.4); t(17)=2.84, p=.014. It appeared that accurately detecting emotion and moderate perspective-taking demonstrating a weaker artificial empathy, such as in the moderate empathetic interaction

(M=3.92), was better than inaccurately detecting emotion and offering high perspective-taking, such as the confused empathetic interaction (M=2.4), in subjects' openness to recommendations. A t-test indicated a statistically significant difference between the two; $t(20)=2.13$, $p=.046$. Low empathetic interaction (M=3.57) also appeared to perform better than confused empathetic interaction (M=2.4) in terms of directional means for openness to recommendations.

# CHAPTER 6

# DISCUSSION

## Conclusions

Hypothesis 1 and 2, regarding high empathetic interactions and their effect on product recommendation openness and acceptance, were not accepted. It appears there is some traction regarding openness to recommendations (e.g., “I have some ideas that may be helpful for you. Do you mind if I share those with you?”) since the means were directionally consistent with the hypothesis, however the data was not statistically significant. The more specific recommendations, such as the deep breathing exercise and the task management app, did not present a clear benefit. Perhaps this could be related to the lack of personalization in the specificities of the individual recommendations.

High empathetic interactions compared to lower empathetic interactions led to increased likability of the AI smart assistant. However, contrary to Brave et al. (2005), subjects did not indicate an increased perception of trust. Therefore, I can only partially accept Hypothesis 3. Perhaps this may be attributed to Picard and Klein’s (2002) theory that AI smart assistants conveying a sense of empathy could be considered inauthentic or appear to still lack understanding of the user’s problem, resulting in less trust. (Picard & Klein, 2002).

It can be confidently stated that, from this research, Hypothesis 4 is accepted. High empathetic interaction versus low empathetic interaction did result in the subjects viewing the AI smart assistant as more intelligent. The notion, predicted in the literature, that emotion detection will likely result in higher perceived intelligence (Picard et al., 2001) has been confirmed through this research. It appears as empathy is introduced to AI smart assistants, users will start to attribute a more general intelligence to this AI, although the technology is still defined as narrow. This circles back to the idea of AI existing on a sliding scale. With emotion recognition society is moving toward a niche between narrow and general intelligence. Even though "emotional AI" as seen in the near future is simply narrow intelligence with the capability to identify and respond to users' emotions, users are developing attitudes toward the technology as more of a social actor than as a machine or computer.

Hypothesis 5, 6 and 7 can also be accepted. High empathetic interaction, compared to low, also increased participants' feelings of support, comfort and understanding from the AI smart assistant. This is a strong indicator that subjects experienced direct effects of artificial empathy regarding sympathetic concern and perspective-taking (de Waal, 2008; Gonzalez-Liencres et al., 2013).

Furthermore, this research was able to determine that emotion detection, despite the level of artificial empathy, increases the AI smart assistant's perceived intelligence, while the combination of accurate emotion detection and strong levels of artificial empathy increases the AI smart assistant's likability as well. This research was also able to determine that accurate emotion detection paired with weak artificial empathy (i.e., moderate empathetic condition) is preferred to the inaccurate emotion detection with strong artificial empathy (i.e. confused empathetic condition), likely due to the fact the emotion synchronization and output are not responsive to the consumers emotional state thereby weakening the appearance of artificial empathy. Therefore, if there is not a high chance of accurately detecting emotion, it may be beneficial to reduce the level of artificial empathy regarding emotion synchronization and output.

## LIMITATIONS

An obvious limitation to this research is the size and demographic of the participant pool. While the Covid-19 pandemic presented us with the interesting opportunity to connect with students on these real-life issues and incorporate them into the simulated interaction, it also created the challenge to gather a significant number of respondents; thereby limiting the condition populations. Furthermore, the participant pool was primarily composed of college undergraduates, which this younger demographic is more trusting of AI technology (Salesforce, 2018). Additionally, individuals under 39 years of age are more receptive to use of biometrics (Petrock, 2019b). Therefore, the demographic within this study may be more receptive to the AI smart assistant.

Another limitation to this experiment was the lack of emotion detection technology - technology that is readily available on many smart devices today. Instead this study attempted to induce an emotion and then mimic that emotion to achieve the appearance of empathy. This resulted in the potential occurrence of unsuccessfully inducing frustration, creating a weaker appearance of empathy. Therefore, I am unable to determine actual causal differences and forced to adopt a quasi-experimental design. There is also risk that subjects were not able to completely and accurately identify their own emotional state. Picard et al. (2001) explains that if subjects have to be asked how they are feeling, the response can vary according to their awareness of feelings and comfort of discussing those feelings, which has the potential to skew results.

## Recommendations for Future Research

I recommend replicating this study with a larger data set. Ideally, I would like to determine if subjects are experiencing the desired consequences of the artificial empathy such as support, comfort and perceived understanding, and what effect this might impose on other downstream variables. For example, what might happen when consumers feel supported due to the presence of artificial empathy and how might this influence the manner in which marketers and brands should interact with consumers.

Additionally, translating the study to voice is another crucial trend to investigate. The majority of AI smart assistants infiltrating consumers' homes are using voice technology, with 48% of US adults owning an AI voice assistant specifically and 35% owning a smart speaker as of 2020 (CivicScience, 2020). Not to mention voice technology, particularly the smart speaker, has been the most installed smart home device in the US since 2018 (Petrock, 2019b). Therefore, it would be useful to compare the effects of voice AI to the chatbot style, textual AI utilized in this study.

It would also be beneficial to test with actual emotion recognition technology. According to Mauss and Robinson (2009), facial expressions and vocal characteristics are two ways to measure human emotion. Not to mention, facial expression and voice tone detection technology are readily available and currently two of the most common emotion detection metrics used to measure affect (Accenture, 2020). Future experiments could be performed in conjunction with Trueface, a facial recognition technology used to determine user emotion, or Behavioral Signals, a technology that is able to detect emotion in voice and speech. Testing with these alternative technologies would give us a more realistic look at the implementation of future technology. It would also eliminate the emotion manipulation, thus increasing the accuracy of the emotion detection, mimicry and, potentially, the overall appearance of empathy. Moreover, if an AI smart assistant is able to assist the user to better identify an emotion, this could perhaps lead to higher satisfaction with purchase decisions prompted by the AI (Seo & Barrett, 2007).

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# APPENDIX A

# EMPATHETIC INTERACTION CONDITIONS

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | **Emotional Empathy** | | | **Cognitive Empathy** | | |
| | | Emotion Detection | Emotion Synchronization | Exemplify Similar Emotional Output | Perspective-Taking | Seek understanding | Seek understanding paired with perspective-taking |
| | Stated Emotion Detection | Based on response to level of Frustration | Emotional Empathy Interaction 1 | Emotional Empathy Interaction 2 | Cognitive Empathy Interaction 1 | Cognitive Empathy Interaction 2 | Cognitive Empathy Interaction 3 |
| | Frustration | (**Accurate:** Frustration level 4 or 5, **Inaccurate:** Frustration level 1 or 2) | (**Present, Absent**) | (**Present, Absent**) | Relevance of Perspective Taking (**High**, **Moderate**) | Seek Understanding (**High**, **Moderate**) | Seek Understading and Relevant Perspective Taking (**High**, **Moderate**) |
| Group 1: High Empathetic Condition | "It sounds like you're a bit frustrated." | Accurate | "Ugh, how annoying! It upsets me to know that is happening to you." | "Argh, I know that can be really irritating!" | "I know trying to manage online courses can be difficult especially when your professor has ridiculous expectations." | "If you could, please write a couple sentences so I can really understand what you're experiencing." | "I want to better understand the whole picture. Please tell me more about the frustrations you have been experiencing and what has been most challenging." |
| Group 2: Moderate Empathetic Condition | "It sounds like you're a bit frustrated." | Accurate | "Hmm, I don't know how that feels." | "Interesting, I'm not sure how to interpret that." | "But, I do know trying to manage online courses can be difficult especially when your professor has ridiculous expectations." | "If you could, please write a couple sentences." | "Please tell me more about the frustrations you have been experiencing and what has been most challenging." |
| Group 3: Confused Empathetic Condition | "It sounds like you're a bit frustrated." | Inaccurate | "Ugh, how annoying! It upsets me to know that is happening to you." | "Argh, I know that can be really irritating!" | "I know trying to manage online courses can be difficult especially when your professor has ridiculous expectations." | "If you could, please write a couple sentences so I can really understand what you're experiencing." | "I want to better understand the whole picture. Please tell me more about the frustrations you have been experiencing and what has been most challenging." |
| Group 4: Low Empathetic Condition | "It sounds like you're a bit frustrated." | Inaccurate | "Hmm, I don't know how that feels." | "Interesting, I'm not sure how to interpret that." | "But, I do know trying to manage online courses can be difficult especially when your professor has ridiculous expectations." | "If you could, please write a couple sentences." | "Please tell me more about the frustrations you have been experiencing and what has been most challenging." |

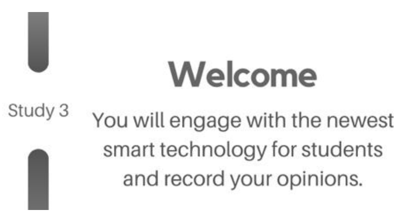
# APPENDIX B

## STUDY INTRODUCTION SLIDES

Figure B1


Figure B2


Figure B3



# APPENDIX C

## MODIFIED PANAS-X ITEM COMPOSITION

| | | | | | |
|---|---|---|---|---|---|
| Frustrated | Irritable | Upset | Dissatisfied | Annoyed | Resentful |
| Guilty | Ashamed | Blameworthy | Angry at Self | Disgusted with Self | Dissatisfied with Self |
| Proud | Confident | Attentive | Alert | Sad | Downhearted |