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Exploring the Effects of Persuasive Designs of Intelligent Advice-Giving Systems on Users' Trust Perceptions, Advice Acceptance, and Reuse Intentions

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EXPLORING THE EFFECTS OF PERSUASIVE DESIGNS OF INTELLIGENT ADVICE-GIVING SYSTEMS ON USERS' TRUST PERCEPTIONS, ADVICE ACCEPTANCE, AND REUSE INTENTIONS

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by

Tian Yu

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To: Dean William G. Hardin III
College of Business

This dissertation, written by Tian Yu, and entitled Exploring the Effects of Persuasive Designs of Intelligent Advice-Giving Systems on Users' Trust Perceptions, Advice Acceptance, and Reuse Intentions, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

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Date of Defense: June 15, 2022

The dissertation of Tian Yu is approved.

Dean William G. Hardin III
College of Business

Andrés G. Gil
Vice President for Research and Economic Development
and Dean of the University Graduate School

Florida International University, 2022

DEDICATION

I would like to dedicate this dissertation to:

My husband Xin who gave me his full support to complete the program, my parents and in-laws who helped us a lot in caring for the kids, and my two lovely kids who were my greatest joy in the hardest times.

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ABSTRACT OF THE DISSERTATION

EXPLORING THE EFFECTS OF PERSUASIVE DESIGNS OF INTELLIGENT ADVICE-GIVING SYSTEMS ON USERS' TRUST PERCEPTIONS, ADVICE ACCEPTANCE, AND REUSE INTENTIONS

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Miami, Florida

Professor George Marakas, Major Professor

With artificial intelligence (AI) penetrating into a broad range of industries in the current age, it has an impact on our daily living in a more and more profound way. Interacting with AI-based systems for advice has become a common practice as well. As advice-giving systems (AGS) become more cognitive and human-like, they can influence users' decision-making to a new level. Therefore, it becomes increasingly important to explore this new type of intelligent system and examine how users perceive and react to the system's persuasive influence. Based on the persuasion knowledge model, this paper identifies various persuasive designs (anthropomorphic features, explanation facilities, and intervention styles) and studies how they affect users' knowledge levels, trust perceptions (cognitive, affective), and eventually their acceptance of advice (behavioral trust) and reuse intentions. The research model has been tested in an online experiment and collected 442 valid responses. In general, the findings give empirical support for the proposed research model in the paper.

The study contributes to (1) the human-computer interaction literature on the effectiveness of different persuasive design characteristics of intelligent AGS. (2) to traditional decision support systems literature on the mechanism that users use to cope with the persuasive influence of the new type of intelligent AGS (persuasive decision-aid systems). (3) to the trust in automation literature by studying various types of trust toward intelligent AGS and their relationships. (4) to the persuasion literature by incorporating the persuasion knowledge model to understand users' attitudes and behaviors toward intelligent agents. (5) to the literature on algorithm aversion and algorithm appreciation by resolving the contradictory findings with a holistic theoretical framework. (6) to the anthropomorphism literature by exploring various aspects of anthropomorphism perceptions on trust. The paper also made insightful implications for practice.

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CHAPTER 1: INTRODUCTION

1.1 Problem Statement

We are entering the age of artificial intelligence (AI) (Gray 2018). As technology advances, AI is getting increasingly sophisticated at dealing with problems that were exclusively for human brains. Moreover, AI is gradually taking over human beings for its ability to solve complex problems but in a more efficient and cost-saving way.

Penetrating into a broad range of industries, such as education, healthcare, finance, and entertainment, AI is influencing our daily living in a more and more profound way. By collecting large amounts of data from both structured and unstructured sources, AI exhibits superb learning and forecasting abilities that are built upon sophisticated statistical models. They can thus achieve high prediction accuracy and provide optimal solutions to users. For example, AI can advise on COVID-19 diagnoses by learning from thousands of chest CT scan images and achieving higher efficiency and accuracy (Li et al. 2020). For more challenging diagnostic tasks of COVID-19, it can detect infection at a speed of two orders of magnitude above human radiologists (Jin et al. 2020).

Advice-giving systems (AGS) are decision support systems that offer users personalized recommendations or advice fitting users' unique requirements or needs (Xiao and Benbasat 2007; Xiao and Benbasat 2014). As AI technology is integrated into AGS, it disrupts our beliefs about what AGS can achieve and provide. These AI-based AGS can provide users with more accurate predictions and give more customized recommendations with their superb forecasting ability. Furthermore, AI-based AGS are more intelligent since they become more adaptive, interactive, and contextual (Schuetz and Venkatesh 2020) while traditional AGS were limited by their requirement of structured inputs from users. Moreover, these intelligent AGS turn out to be more cognitive and human-like. They can interact with users more naturally, building a more intimate relationship with users. These advances create great potential for AGS to aid and even exert influence on decision-making. In other words, intelligent AGS can persuade people to take system advice and use personalized arguments to make in-time interventions. For example, in a field study of more than 6,200 customers of a financial service company, intelligent system agents deployed adaptive selling strategies and were four times more effective than inexperienced workers in persuading customers to buy the financial products (Luo et al. 2019).

While AI-based AGS are so intelligent that they affect human decision-making to a new level, it becomes increasingly important to cast our attention to understanding how users perceive and eventually adopt these new types of systems.

1.2 Significance of the Problem

As AI-based AGS exhibit more intelligence and create tremendous upside potential to influence decision-making, it’s still not clear how people perceive and react to it. Research has found people are averse to taking advice from algorithms or systems when being informed of the real identity of the interacting agent (e.g. Dietvorst et al. 2015; Longoni et al. 2019; Luo et al. 2019). This stream of research summarized their findings as “algorithm aversion”. Another set of research found the opposite result and termed it “algorithm appreciation” when the advice provided by algorithms is preferred in various contexts (e.g. Castelo et al. 2019; Logg et al. 2019). For a review of the contradictory findings on whether people prefer to take advice from advice systems or human beings, see Jussupow et al. (2020). However, most papers studying whether people like to take advice from AGS followed a phenomenological approach. It is thus crucial to take a theoretical lens to explore the mechanism which people use to determine their acceptance of advice from intelligent AGS. It is important to understand how users perceive intelligent AGS and how these perceptions might influence their acceptance of advice and adoptive intentions of the systems.

To fill this gap, I take a "trust perspective" to approach the problem. As establishing trust in the technology has taken the center stage in IS research in the past few decades, it is still necessary to look into novel antecedents of trust as well as the new contexts of trust study (Benbasat et al. 2010). Moreover, traditional trust research primarily investigated the cognitive aspect of trust, leaving the affective aspects of trust largely disregarded. While cognitive trust is based on one's rational assessment of the competence of the partner to be relied upon, emotional trust refers to emotional feelings of comfort, security, or perceived strength of the relationship with one's partner (Lewis and Weigert 1985). As intelligent AGS gain more resemblance with human beings and become more natural in interacting with users, it's getting more urgent to explore emotional trust which is more consequential to predicting behaviors in interpersonal relationships (McAllister 1995). In addition, the adoption of a complex new type of system requires a "leap of faith" which cannot be cognitively understood (Hoff and Bashir 2015; Lee and See 2004b). Besides exploring emotional trust, I also include behavioral trust as the third component of trust in the paper. The exploration of both cognitive trust and emotional trust leads naturally to behavioral trust, which refers to actions that emerge from cognitive trust and emotional trust (Lewis and Weigert 1985). In the context of AGS, behavioral trust has been commonly measured as users' acceptance of advice from AGS (e.g. Logg et al. 2019).

As the influence intelligent AGS exert on users is persuasive in nature, I adopt the persuasion knowledge model (Friestad and Wright 1994) as our framework to develop our persuasive designs. The persuasion knowledge model (PKM) is widely cited in the marketing or psychology literature but has been rarely adopted in the IS research field, missing a great potential to use its theoretical lens to study persuasion perceptions. It extends traditional persuasion theories such as the Elaboration Likelihood Model (Petty and Cacioppo 1986) or Heuristic-Systematic Model (Chaiken 1987) which only focus on customers' topic attitudes. PKM adds the task of refining agent attitudes as a basic goal of decision makers since it is also intuitive to seek valid attitudes about the influencing agent, especially when people are unfamiliar with the agent or unable to understand or evaluate the topic of interest under persuasion attempts. This fits the situation whereas intelligent AGS is a new form of technology for users and offers advice based on data analysis from diverse and dynamic sources beyond human synthesis.

According to PKM, the outcomes of persuasion would be influenced by three knowledge levels established by the receivers of persuasive messages: agent knowledge, topic knowledge, and persuasion knowledge. Agent knowledge consists of receivers' beliefs and perceptions about the persuasion agent. Topic knowledge refers to beliefs about the message topic. Persuasion knowledge refers to beliefs about a persuasive attempt such as the agent's motives, appropriateness of the tactics, and receivers' own coping mechanisms

(Campbell and Kirmani 2000). The three knowledge structures together determine persuasion outcomes.

To motivate users of AGS to accept system recommendations, designers endeavor to enhance the persuasiveness of a system by implementing various design features. This study classifies these design features into three major categories: anthropomorphic features, explanation facilities, and intervention styles, each targeting a specific knowledge level. In particular, I design anthropomorphic features (e.g. avatar-based agent with emotion expressive responses) to influence users' perception of the virtual agent; explanation facilities to add topic knowledge for users, and intervention styles to influence users' persuasion knowledge levels. Prior literature has provided limited understanding with respect to the effects of persuasive features of AGS on users' knowledge levels. None of them has adopted a PKM lens and explored how users' change in knowledge levels may consequently influence various dimensions of trust (emotional, cognitive, and behavioral) and reuse intentions of AGS. In this study, the persuasive designs of AGS were incrementally added to experimental conditions aiming to influence users' knowledge levels of each category.

1.3 Research Questions

This study aims to answer the following research questions:

1. How can persuasive designs of intelligent advice-giving systems influence users' knowledge levels under persuasion?

2. What are the effects of users' knowledge levels on their trust perceptions (emotional trust and cognitive trust) and reuse intentions of intelligent advice-giving systems?

3. What are the effects of users' trust perceptions (emotional trust and cognitive trust) on their acceptance of advice (behavioral trust) and what factors might moderate the relationships?

I propose a theoretical model under the PKM framework and proposed persuasive design features that may increase users' knowledge level of different categories and consequently influence users' trust (cognitive, affective, and behavioral trust) as well as future adoption intentions toward intelligent AGS. The research model has been empirically tested by online experiments and collected 442 valid responses.

1.4 Research Contributions

By answering these research questions, this study makes both theoretical contributions and provides insightful implications for practice.

Theoretically, this study's contribution to the literature is in several ways. It seeks to contribute to:

(1) the human-computer interaction literature on the effectiveness of different persuasive design characteristics of intelligent AGS. This research put focuses on anthropomorphic features, explanation facilities, and intervention styles and explores how these features influence the knowledge levels of users under persuasion. Furthermore, I investigate how the users' developed knowledge during persuasion can influence their trust perceptions

(emotional trust and cognitive trust), acceptance of advice (behavioral trust), and future adoption intentions of intelligent AGS.

(2) to traditional decision support systems literature on the mechanism that users use when being under the persuasive influence of the new type of intelligent AGS (persuasive decision-aid systems). In particular, I proposed a research model that lists out factors that lead to users' trust perceptions and eventually their reuse intentions toward intelligent AGS.

(3) to the trust in automation literature by studying various types of trust toward intelligent AGS. Specifically, I treat emotional trust, cognitive trust, and behavior as distinct constructs that each has different antecedents and consequences.

(4) to the persuasion literature by incorporating the persuasion knowledge model to understand users' attitudes toward intelligent agents. I demonstrate how three knowledge structures (agent knowledge, persuasion knowledge, and topic knowledge) work together to shape users' agent attitudes (emotional trust) as well as topic attitudes (cognitive trust).

(5) to the literature on algorithm aversion and algorithm appreciation by resolving the contradictory findings with a holistic theoretical framework. I investigate factors that lead to people's acceptance of advice from an algorithmic source (intelligent advice-giving system) and moderators of relationships.

(6) to the anthropomorphism literature by exploring various aspects of anthropomorphism perceptions on trust. In particular, this study breaks the perception of anthropomorphism into more distinctive perceptions (closeness, mind perception, and social presence) and studies which perception has more impact on emotional trust.

Considering the study's practical implications, I provide insights to designers of intelligent AGS on persuasive design characteristics that lead to trust perceptions, acceptance of system advice, and future reuse or adoption intentions. I also specify how user characteristics may play a moderating role so designers can target them efficiently.

The rest of this dissertation is organized as follows: Chapter 2 reviews the literature on trust. Chapter 3 lays the theoretical foundation of the paper using the persuasion knowledge model and proposes persuasive designs. The research model and hypotheses are developed in Chapter 4. After that, I explained the research methods in Chapter 5, and the result analysis was presented in Chapter 6. Discussion, future research directions, and conclusions were presented in the last three chapters.

CHAPTER 2: LITERATURE REVIEW

This study attempts to explore users' different types of trust in intelligent advice-giving systems, and the literature review survey the relevant and major prior works on trust: how this concept was developed and brought into the technology domain and then the IS field and the specific context (advice-giving systems) of this research. While trust is a broad concept and is intensively studied in various social and science disciplines, I focus on a few areas (i.e., interpersonal interaction, automation, information systems, and advice-giving systems) upon which the model framework is developed.

2.1 Trust Research in Interpersonal Interaction

The most natural context in which trust is studied is interpersonal interaction. Indeed, this is a vast stream of literature. I review a number of fundamental papers that are closest to this study.

Lewis and Weigert 1985

Lewis and Weigert (1985) discussed various dimensions of trust and came up with a sociological conceptualization of interpersonal trust. The conceptualization recognized the multi-faceted character of trust that includes cognitive, emotional, and behavioral aspects as foundations of trust.

Cognitive trust is based on a cognitive process when we try to find "good reasons" or evidence of trustworthiness to trust a person. It involves cognitive familiarity or certain knowledge levels with the object of trust. In other words, if we know nothing about the object of trust, we have no reason to trust. On the other hand, the additional knowledge we gain may not lead to trust, because there is usually a cognitive gap from the expectations simply led by experiences.

Emotional trust is another sociological foundation of trust. Being somewhat a complement to the cognitive base, it is an emotional bond between all participants of a relationship. This affective component of trust can be intense in interpersonal trust. Betrayal or abuse or violation of trust occurring after emotional investments of trust would result in emotional outrage or pain and destroy the very basis of the relationship.

Lastly, the behavioral aspect of trust is to perform a series of actions under risk, hoping or being confident that the person to be trusted will act competently and dutifully. Interestingly, behavioral trust serves as a connecting bridge between cognitive and emotional trust. It may be activated primarily by cognitive trust (good rational reasons concerning the merits of the object of trust), emotional trust (strong positive affection for the object of trust), or a mixture of both. On the other hand, behaviors facilitate the formation of the cognitive platform of trust and help establish/reinforce the emotional feeling of trust. In other words, we are willing to trust others more if we can observe certain actions from them implying that we have their trust because their acts have made us more likely to act reciprocally and conduct the trust behaviors as a return.

McAllister 1995 (organizational context)

McAllister (1995) explored the factors that affect the development of trust in the organizational context. It studied the relationship between managers and professionals and discussed its nature and function in terms of interpersonal trust in organizations, and how it leads to trust behaviors and performance. In the theoretical model, trust based on affect/emotion and trust based on cognition has distinct antecedents and consequences. See Figure 1 for a visual illustration of the structure of McAllister (1995).

Peer’s citizenship behavior toward the manager and the interaction frequency between them are considered to be the two antecedents of the affect-based trust of a manager. On the other hand, trust based on cognition has three antecedents: the extent of that peer's performance in showing reliability, the extent of social similarity (culturally or ethnically), and the peer’s professional credentials. Cognition-based trust was also viewed as "more superficial”, which would lead to trust based on affect (rooted in an individual's attributions about others' behavior motives). Emotional trust is more persistent since the recognized motives are often considered true and permanent.

McAllister (1995) also proposed district consequences of the two types of trust (affect and cognition-based) in the managerial context. A manager having more cognition-based trust in a peer will reduce control-based monitoring and refrain from defensive action toward that peer. On the other hand, a manager having more affect-based trust in a peer will increase the need-based monitoring and exert more citizenship behavior on that peer interpersonally. The paper also argues that only interpersonal citizenship behavior and need-based monitoring are associated with peer performance, pointing out the significance of building affect-based trust within organizations.

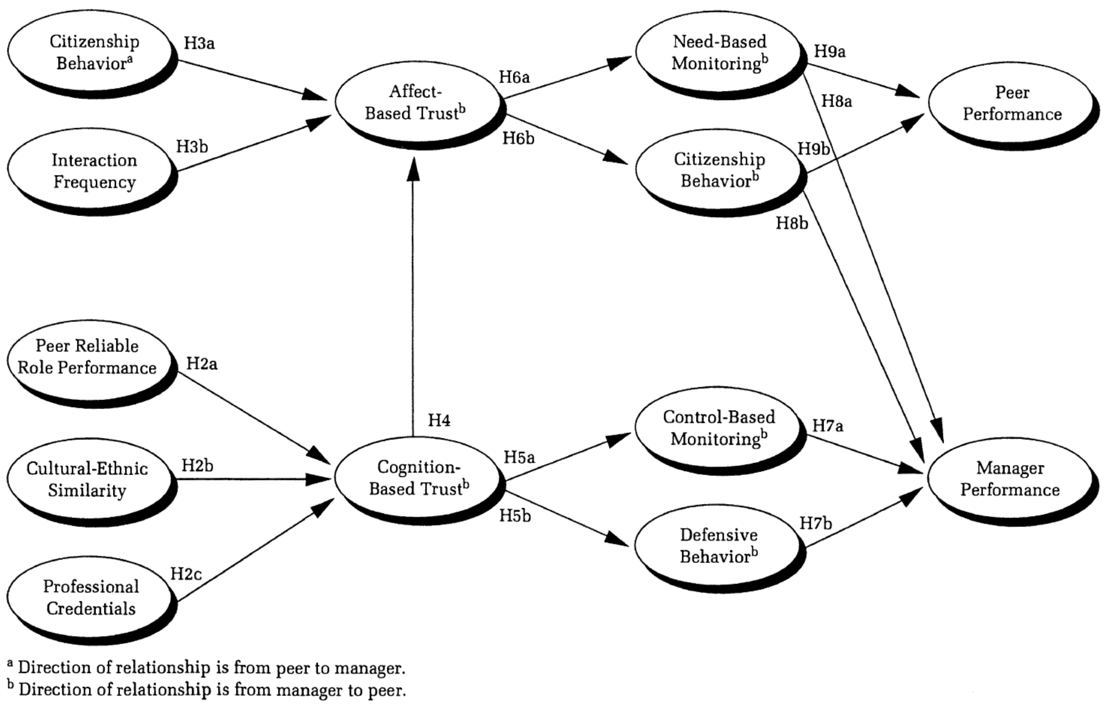


Figure 1 Research Model Extracted from McAllister (1995)

<u>Johnson and Grayson 2005 (consumer context)</u>

Johnson and Grayson (2005) investigated interpersonal trust in the context of consumer relationships in service settings, which also has both cognition and affect bases. See Figure 2 for a visual description of their research model. They have empirically demonstrated emotional trust is operative independently of cognitive trust, which is the willingness (or confidence) of a customer to count on a server's competence (or reliability). Its antecedents include service provider's professionalism, service performance, reputation of the provider, and past experiences about the interactions. While reputation of the provider and experiences from past interactions also contribute to emotional trust, similarity (i.e., common interests and values between customer and service provider) would only lead to emotional trust rather than cognitive trust. In their model, both cognition-based and emotional trust in the service provider is positively associated with the customer's expectation of interactions in the future.

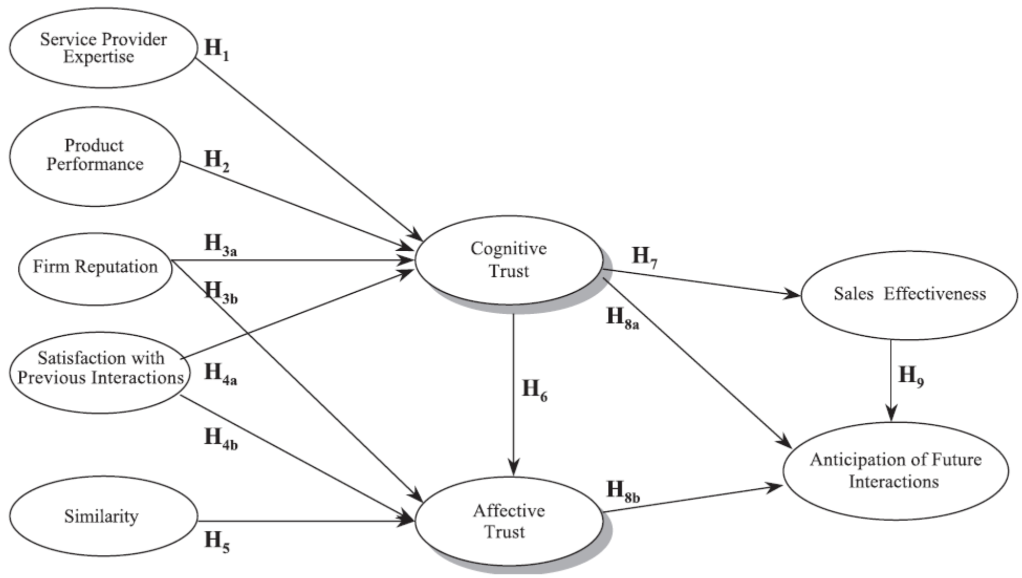


Fig. 1. A model of customer trust in service providers.

Figure 2 Research Model Extracted from Johnsona and Grayson (2005)

Mayer et al. 1995

The definition of trust by Mayer et al. (1995a) emphasizes the importance of the actions at stake and people's willingness to be vulnerable. It is the "willingness of a party to be vulnerable to the action of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (p. 712). The paper was written for the organizational context but the definition goes beyond the interpersonal context for the concept of trust. This creates an opportunity for us to consider trust with regard to trust in automation or technology.

Three elements of trust, namely, ability, integrity, and benevolence were proposed by Mayer et al. (1995a). See Figure 3 for details. Trust exists only when these three elements are present. Ability is a domain-specific characteristic of the trustee related to technical skills and competencies needed to perform some task in the domain of interest. This means that the trustee must know or be an expert in the field important to the trustor. Benevolence is defined as the degree to which the trustor believes that the trustee seeks to do good things besides an individual profit motive. Benevolence has to do with altruistic motives and good intentions of trustees perceived by trustors. Integrity is about the extent the trustor observes that a set of acceptable rules/principles is closely adhered to by the trustee. While these three factors are bound to vary independently, this does not mean that they are independent of each other; each of the three can vary along a continuum, and trustworthiness is holistically expected to also vary along a continuum, a party is more or less trustworthy, as opposed to being trustworthy or not.

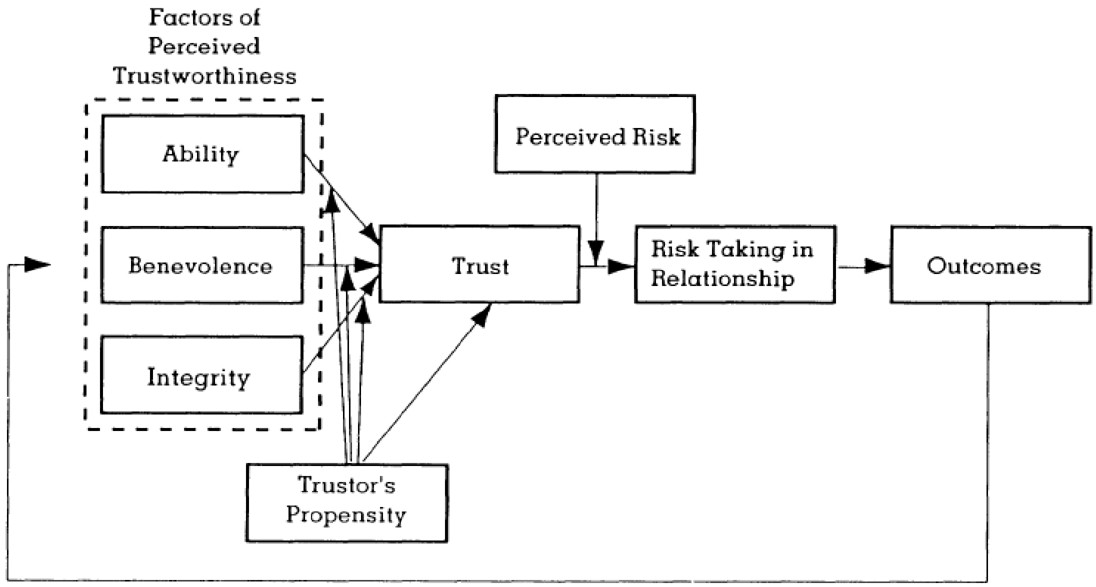


Figure 3 Research Model. Image Originally from Mayer et al. (1995a)

2.2 Trust in Automation

Lee and See 2004

As an extension of Mayer et al (1995a) and Lee and Moray (1992), Lee and See (2004a) generalize the concept of trust to apply in the context of automation, which includes the studies on technology and automated systems (i.e., non-human objects). Note that their developed concept of trust still contains categories introduced in the prior works. Specifically, trust in their paper refers to "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" (p. 54). In addition, by summarizing the existing research, Lee and See (2004a) claimed that prior beliefs about trust can be categorized into three groups, labeled as performance, process, and purpose, which are defined one by one below.

First, the overall operations record of the automation, e.g., whether it is reliable, how predictable it is, and its ability to deal with problems, constitutes the notion of performance. Second, the appropriateness of the automation in its essential functioning for the job it is facing, which includes the belief of how consistent it is, defines the process. Trust that concerns the process is given to the agent itself rather than its performing behaviors. Third, whether the automation is employed in the intended (by designer) areas or not, and if yes, how much, is referred to as purpose. This notion describes the origin of automation and corresponds to beliefs previously studied in the literature. In fact, take Mayer et al. (1995) for example, the concepts of ability, integrity, and benevolence proposed in that paper correspond to performance, process, and purpose, respectively.

2.3 Trust Research in IS Field

Trust is not a new concept in the field of IS. I conduct a systematic review of the extant literature by searching the eight journals listed by AIS as senior scholars' basket of journals, which are listed alphabetically in the following:

European Journal of Information Systems

Information Systems Journal

Information Systems Research

Journal of AIS

Journal of Information Technology

Journal of MIS

Journal of Strategic Information Systems

MIS Quarterly

I only include papers with "trust" in the title as a keyword for the search and obtained 120 papers in total. The papers were published between 1998- 2020 (data search on 3/30/21). The paper count for each journal was listed below:

Table 1. Journal Name and Paper Count

Journal Name	Count
European Journal of Information Systems	18
Information Systems Journal	17
Information Systems Research	18
Journal of AIS	10
Journal of Information Technology	4
Journal of MIS	31
Journal of Strategic Information Systems	9
MIS Quarterly	13
Total	120

The concepts of trust were brought into IS research to study trust in the online field such as e-commerce and online marketplaces (Gefen et al. 2008; Wang and Benbasat 2007). There has also been an examination of trust in online decision support systems such as recommendation agents (e.g. Wang and Benbasat 2005; Wang and Benbasat 2008; Xiao and Benbasat 2007). While most theorizations of trust are about trusting beliefs (e.g. McKnight et al. 2002) in the IS field, there has been some study investigating the different dimensions of trust and exploring their distinct antecedents and consequences (e.g. Komlak and Benbasat 2006; Wang et al. 2016). Since websites or online systems aim to influence users to achieve certain behaviors, some research adopts a persuasion view to study user perceptions in the online environment. While persuasion outcomes are mostly measured by the change of attitude or evaluations in the psychology and marketing domains, IS researchers use trust as a measure of persuasion outcome (e.g. Kim and Benbasat 2009; Wang et al. 2016). In discussions, cognitive trust is conceptualized as beliefs and emotional trust as attitudes, which would further influence behavioral intentions. These theorizations justify the use of various components of trust as suitable measures of persuasion outcomes.

Komlak and Benbasat 2006

Komlak and Benbasat (2006) propose a theoretical framework on how the personalization and familiarity perceived by users affect two types of trust, i.e., cognitive and emotional trust. See Figure 4 for a description of their model. Furthermore, they conduct empirical studies to investigate such effects and show that users are willing to adopt the recommendation agent because of the two kinds of trust. The paper is the first paper that brings the concept of emotional trust to IS literature and emphasizes the role of emotional trust in IT adoption.

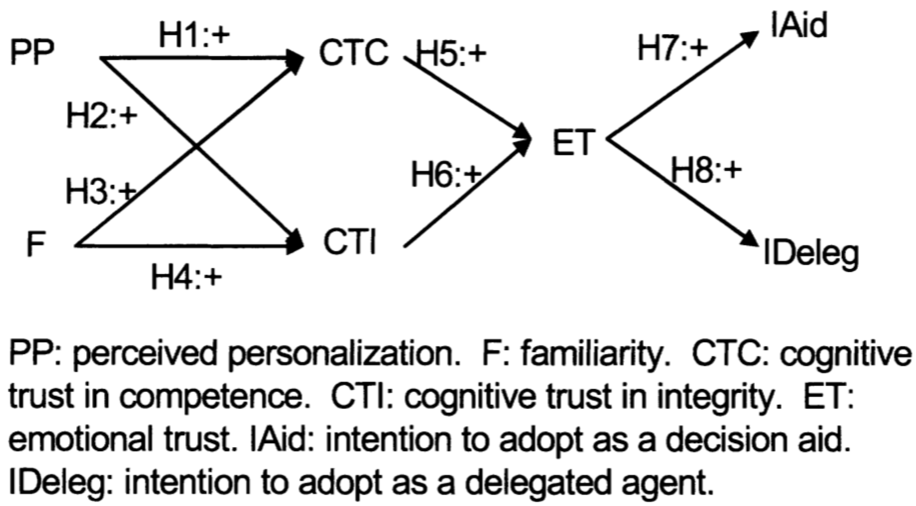


Figure 4 Research Model Extracted from Komlak and Benbasat (2006)

<u>*Wang et al. (2016)*</u>

Wang et al. (2016) scrutinize the relationship between object-based beliefs (such as cognition and affect-based trust) and the design characteristics (i.e., explanation facilities and avatar interfaces). See Figure 5 for the visualization of their model framework. The latter are two attributes corresponding to rational and social appeals, respectively. They find that rational appeals reflected by the explanations can influence both object-based beliefs significantly; but affect-based trust will not be affected much by an avatar (social appeals) alone unless the avatar is perceived as highly professional, in which case the impact could be considerable. Moreover, Wang et al. (2016) also identify that the two beliefs have contrasting impacts on the users' perception regarding the usefulness of the recommendation agent and the enjoyment of using the agent. Specifically, compared to the other belief, affect-based trust has a larger impact on the perceived enjoyment, whereas cognition-based trust has a larger impact on the perceived usefulness.

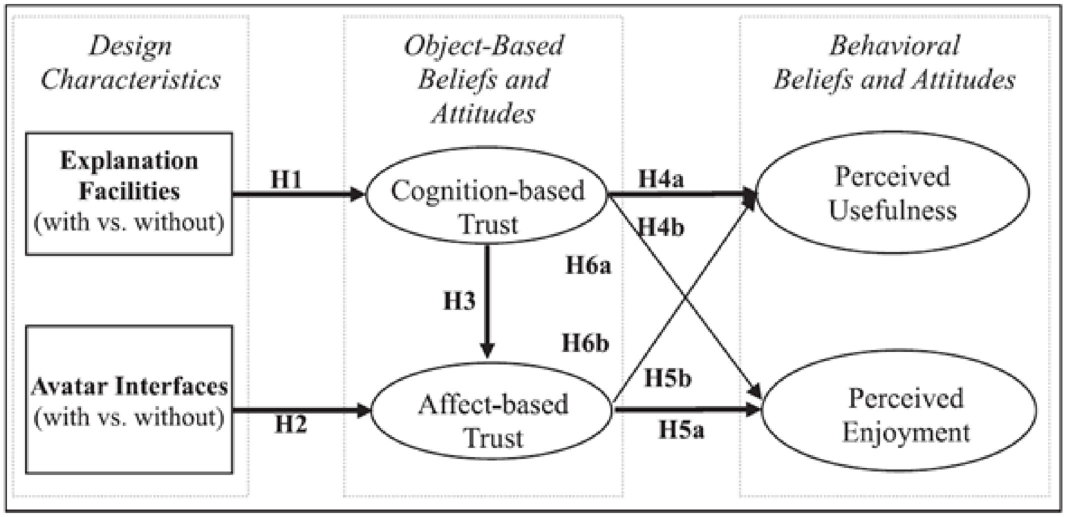


Figure 5 Research Model Extracted from Wang et al. (2016)

CHAPTER 3: THEORETICAL FRAMEWORK

3.1 Persuasion Knowledge Model

Friestad and Wright (1994) is one of the seminal papers where the persuasion knowledge model is rooted and developed. Borrowed from consumers' theories in marketing, the persuasion knowledge model postulates that consumers will use a variety of developed knowledge structures to deal with situations where they are being persuaded. For example, in presence of an advertisement or other marketing attempts, consumers will consult their knowledge about the advertising topics and the marketing agent. To be specific, there are three knowledge structures developed by the consumers in order to achieve attitude refinement goals: agent knowledge, topic knowledge, and persuasion knowledge. See Figure 6. Note that the outcomes of a persuasion situation hinge on the above three knowledge structures. First, agent knowledge refers to consumers' beliefs about the persuasion agent; e.g., the traits of the marketer, whether the marketer is competent, and what are the marketer's goals. Second, topic knowledge includes beliefs about the topic of the persuasion; e.g., the products/services being promoted. Third, persuasion knowledge can be loosely defined as a set of beliefs or consumers' intuition about persuasion; e.g., what the consumers think of the agent's motivation, the persuading tactics and whether they are appropriate, and the way the consumers themselves cope with the persuasion (Campbell and Kirmani 2000).

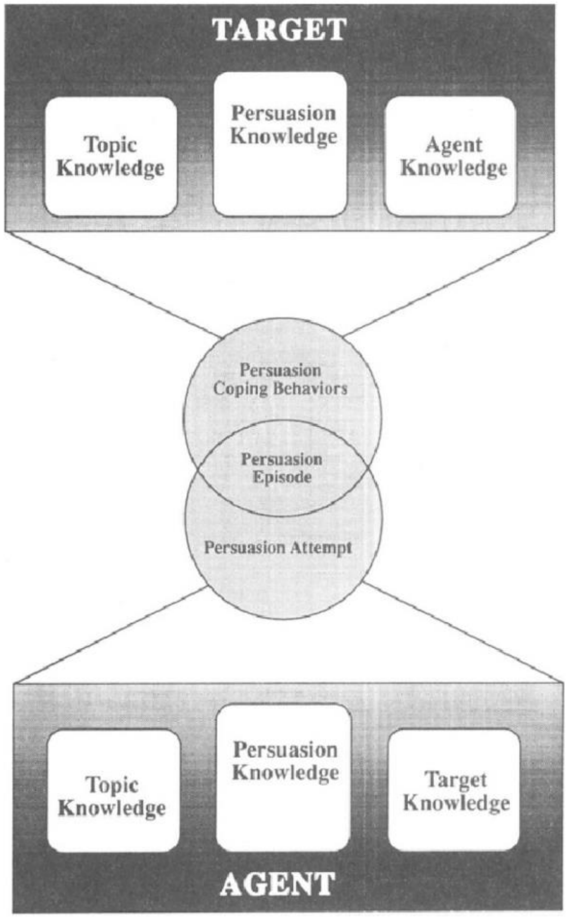


Figure 6 Research Model Extracted from Friestad and Wright (1994)

It is interesting to compare the persuasion knowledge model with traditional theories on persuasion, such as the elaboration likelihood model (Petty and Cacioppo 1986) or the heuristic-systematic model (Chaiken 1987). The two traditional models primarily focus on consumers' attitudes towards the persuasion topic. They argue that consumers will try to refine the topic attitude by either engaging elaborative hints or forming heuristics. In this regard, the persuasion knowledge model extends the theories to include agent attitude refinement as consumers' basic behavior under persuasion. Naturally, such refinement is much needed and especially common when there is little (and maybe inaccurate or outdated) information about the persuading agent. As such, according to the persuasion knowledge model, consumers try to refine their topic or agent attitude through elaborative or heuristic processing.

3.2 Persuasive Design of AGS

In this study, I explore persuasive designs that may influence the knowledge levels of persuadees in decision-making. Past literature has well employed anthropomorphic features to increase the anthropomorphic perception of an intelligent agent. Explanation facilities are features that provide explanations to users when persuading them to accept system recommendations. It includes “how” explanations on how the system reached its recommendation and “why” explanations on why the recommended option would fit the user the best. The third design to be explored in the study is intervention styles. When the system intervenes in users’ decision-making, it can use different styles to send persuasive messages or interact with users. The two styles adopted in the study are the “facilitative” style and the “authoritative” style. By taking the “authoritative” style, the system would take on the role of authority and push users to obey its decision. On the other hand, by taking the “facilitative” style, the system would serve as an assistant and tries to help users and request them to consider its advice.

These three design features are addressed as persuasive designs in this study under the context of intelligent AGS persuading users to take system advice. The three persuasive features aim to influence people’s knowledge levels of different categories during persuasion. Anthropomorphic Features target people’s agent knowledge and perception.

Explanation facilities aim to increase people's topic knowledge. Intervention styles attempt to influence people's persuasion knowledge. See Figure 7 for an illustration.

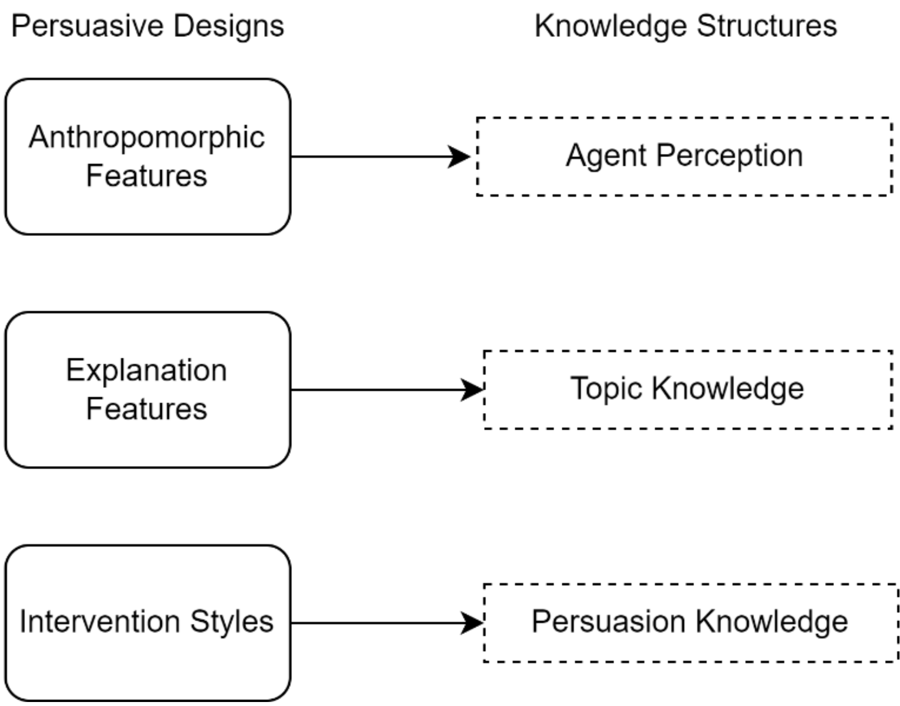


Figure 7 Persuasive Designs on Knowledge Levels

3.2.1 Anthropomorphic Features

Anthropomorphism is the attribution of humanlike characteristics such as cognitive and affective states to nonhuman agents or entities (Epley et al. 2007). It is prevalent for users to develop a perception of human-likeness in the process of interactions. The main factors or the three psychological determinants that cause people to be more likely to anthropomorphize are accessible anthropocentric knowledge, effectance motivation, and sociality motivation (Epley et al. 2007). The anthropomorphic perceptions could be driven by various design features (for a review, see Blut et al. 2021): physical features (such as making the avatar more human-like); behavioral features (such as mimicry of human interactions); and intentional framing (such as giving a virtual agent a human name).

Physical Features

It is relatively intuitive that the physical representation or embodiment of a system can affect how much it can be anthropomorphized. Research has shown that the presence of an avatar can increase the perceived human-likeness of a virtual agent (e.g. Morana et al. 2020; Nowak and Rauh 2005). It's natural to assume that the more human features a virtual agent possesses, the more strongly it is anthropomorphized. However, there is an "uncanny valley" effect found in past research, that a highly humanlike robot or system may cause discomfort and fear to users (Mori et al. 2012). Past research also studies andromorphic perceptions using static robot pictures, cartoon avatars, or real human pictures. Using cartoon avatars was found to create the highest level of trust and likeness (De Visser et al. 2016).

Behavioral Features

Behavioral features mainly refer to a system or a virtual agent that exhibits behavioral characteristics of human beings, such as mimicry of human interactions and using human voice or gestures. Past studies found that a system or a virtual agent can be perceived as more humanlike than when showing their abilities to engage in interactions naturally as humans (Dehn and Van Mulken 2000). Furthermore, when a system acts emotionally expressive, it's more likely to be perceived as human-like. For example, Novikova (2016) reported that users' anthropomorphic perceptions were significantly higher when a robot showed its feelings than a nonemotional robot. Moshkina (2011) found that when a system showed an extroverted personality, it is more likely to be perceived as humanlike than one with an introverted personality.

Intentional Framing

As suggested by Epley et al. (2007), simply implying using anthropomorphic descriptors may prompt message receivers to model the object as human-like. Research has also successfully anthropomorphized an autonomous vehicle by giving it a name and a voice (Waytz et al. 2014).

3.2.2 Explanation Facilities

Explanations are important components of decision support technologies, including AGS, because explanations can make the technologies transparent to their users. Wang and Benbasat (2007) have investigated the explanation facilities for an online recommendation agent (RA) that can enhance its transparency. The explanations were provided to clarify the line of reasoning used by the RA based on the users' preferences (i.e., "how" explanations), justify the purposes of the questions posed by the RA to the users (i.e., "why" explanations), and help users choose among and use different RA features (i.e., "guidance"). Intelligent AGS can use explanation facilities to inform users. For example, it can use two-sided arguments or provide evidence of suitability or prior statistics on the recommended option as a reference.

3.2.3 Intervention Style

When an advice-giving system tries to persuade the users, it needs to intervene in users' decision-making in some way. Intervention styles are the ways like the tone of the conversation that the system adopts to prompt or urge users to change their decisions. In particular, this study focus on two types of styles: authoritative and facilitative (Heron 1976).

The authoritative style is rather more hierarchical. The persuader takes the responsibility for and on behalf of the persuadee, guides his or her behavior, gives instructions, and raises consciousness. In this sense, the persuader tries to be the authority and expects the persuadee to obey. The facilitative style, on the other hand, is less hierarchical. The persuader would seek to assist the persuade by enabling him or her to become more autonomous and take more responsibility. As an example, the persuader may request decision change by emotionally acknowledging the feelings of the persuadee and presenting relevant information to assist their cognition.

CHAPTER 4: RESEARCH MODEL AND HYPOTHESES DEVELOPMENT

4.1 Research Model

I build the research model based on persuasive designs, persuasion knowledge model, and trust literature. This research aims to develop three persuasive designs to influence different knowledge levels (agent, topic, and persuasion). To be more specific, the anthropomorphic features aim to influence agent knowledge and perception; the explanation facilities target adding topic knowledge and the intervention styles attempt to influence persuasion knowledge. The change in knowledge levels in each category will then have an impact on people's trust perceptions.

According to PKM, the two goals of people under persuasion are developing valid topic attitudes as well as valid agent attitudes. I argue that emotional trust, the feeling of security to rely on the influencing agent (i.e. intelligent AGS), pertains to agent attitude. Cognitive trust, on the other hand, is a set of beliefs that the intelligent AGS provide good recommendations, which pertains to topic attitude. In the cognitive process, users attempt to evaluate the quality of the given advice, which determines their assessment of competency of the system at the advising job (i.e. cognitive trust). When users are motivated to form valid agent attitudes, they are motivated to form perceptions and gain knowledge about the agent. Their persuasion knowledge can also influence their evaluation of the agent. These two types of knowledge would thus directly influence the formation of emotional trust. On the other hand, to form valid topic attitudes, users tend to develop topic knowledge. Their persuasion knowledge may also affect how they assess the topic of interest. Therefore, both topic knowledge and persuasion knowledge would influence cognitive trust levels.

The key assertions of the research model are (1) experimental conditions with various design features lead to different levels of users' knowledge in each category; (2) agent perception (anthropomorphism) leads to emotional trust; (3) persuasion knowledge (perceived benevolence, perceived integrity and perceived control) leads to both emotional trust and cognitive trust; (4) topic knowledge (perceived understanding) leads to cognitive trust; (5) both cognitive and emotional trust lead behavioral trust and reuse intention; (6) trust propensity moderate the relationship between emotional trust and behavior trust while topic expertise moderate the relationship between cognitive trust and behavior trust. The model guides the hypothesis development below.

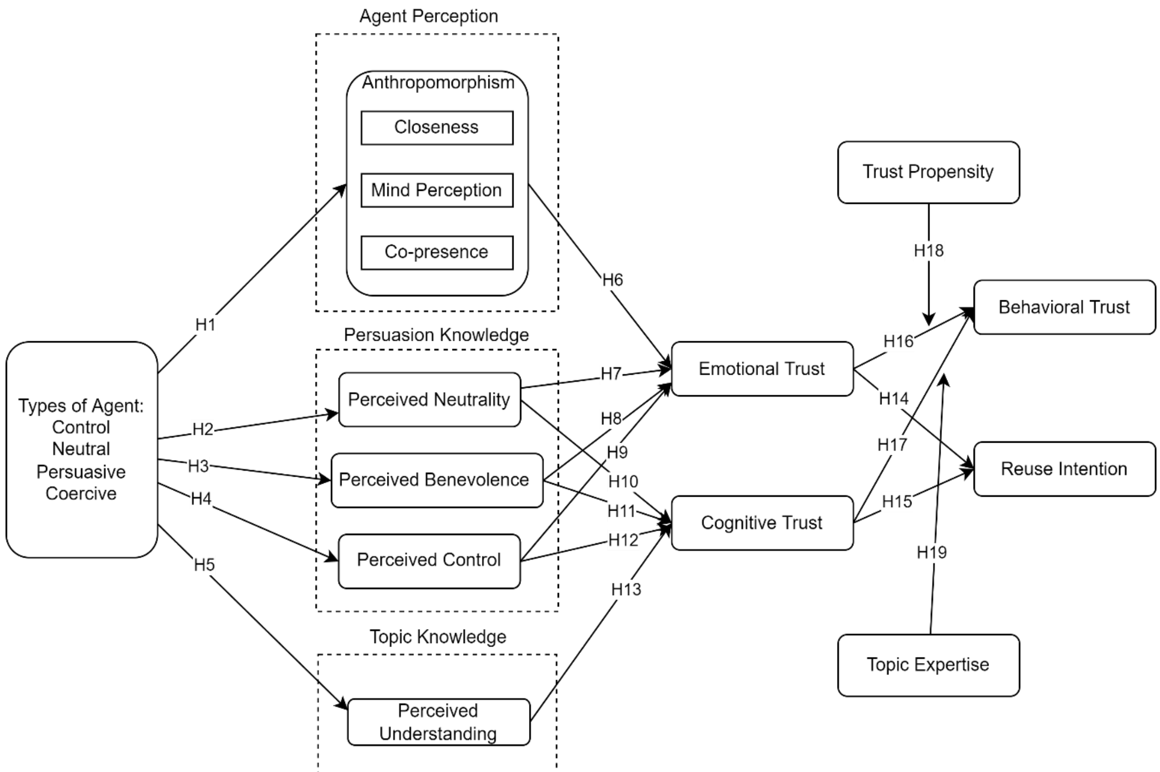


Figure 8 The Conceptual Research Model

4.2 Hypotheses Development

4.2.1 Experiment Conditions

I designed four types of intelligent AGS to create the different levels of knowledge in each category: control condition, neutral condition, persuasive condition, and coercive condition.

In the control condition, the system didn't have an avatar presence, users were told that the output of the system was generated from algorithmic calculations and the picture that users see was a picture of digital nodes of computers (see Figure 8 for representation). In the neutral condition, a virtual agent had an animated avatar and was responsive and emotionally expressive to users' inputs. However, the virtual agent just presented her recommendation without explanation and didn't attempt to persuade the participants to take her advice. In both the persuasive and the coercive conditions, I adopted the same anthropomorphic features as in the neutral condition. Moreover, I added the explanation facilities that persuade users to adopt the virtual agent's advice and provide them with explanations. The difference between persuasive condition and coercive condition was the different intervention styles they adopted. A persuasive intelligent agent took the assistant role and tried to influence users to choose the option that the agent recommends in a gentle and informative way. On the other hand, a coercive intelligent agent acted as an authority and expert and tried to demand users to choose the recommended option. The four experimental conditions with design features are listed in Table 1 below.

Table 1 Experimental Conditions with Design Features

Conditions	**Anthropomorphic Features**		**Explanation Facilities**	**Intervention Styles**
	Agent Representation	**Agent Interaction**		
Control	System Picture Without a Human Name	Plainly Asking Questions	No Explanation	No Intervention
Neutral	**Animated Avatar with Bubble Text**	**Responsive and Emotionally Expressive**	No Explanation	No Intervention

Persuasive	Animated Avatar with Bubble Text	Responsive and Emotionally Expressive	**Persuade by Providing Explanations**	**Facilitative**
Coercive	Animated Avatar with Bubble Text	Responsive and Emotionally Expressive	**Persuade by Providing Explanations**	**Authoritative**

As different persuasive design features target knowledge levels in different categories, users' knowledge levels are proposed to vary across conditions. The control condition is hypothesized to have low knowledge levels in all three categories (agent, topic, and persuasion). The neutral condition has anthropomorphic features and thus is proposed to have a high level of agent perception. Both persuasive and coercive conditions have explanation facilities and thus users are supposed to have a high level of topic knowledge in the two conditions. Since the coercive condition takes an authoritative style, it's supposed to induce higher persuasion knowledge levels in users. The expected knowledge levels of each experimental condition are listed in Table 2 below.

Table 2 Proposed Knowledge Levels Induced by Each Condition			
Conditions	Anthropomorphism Perception	Topic Knowledge	Persuasion Knowledge
Control	Low	Low	Low
Neutral	High	Low	Low
Persuasive	High	High	Low
Coercive	High	High	High

4.2.2 Effect of Experimental Conditions on Knowledge Levels

There are various aspects of anthropomorphism perception (Lee et al. 2006). In this paper, I include three dimensions: closeness, mind perception, and co-presence. Closeness focuses on the emotional closeness one feels when interacting with the system. People perceiving high closeness consider the interacting system to be friendly and want to have a conversation with the system (Lee et al. 2020). Mind perception is the extent to which the intelligent AGS can be perceived to be able to think and engage in mental activities. Social presence is the extent to which a human believes that someone is present (Heerink et al. 2008). It is to perceive systems as present and in one's company (Lee et al. 2006).

In this study, I use different ways to compose the anthropomorphic features. Anthropomorphic features aim to increase anthropomorphism perceptions. The virtual agent will first be introduced to users with a name (intentional framing) and interact with users with an animated avatar (physical features). During the interactions, she is responsive to users' answers and can express her feelings (behavioral features). These features are supposed to increase users' anthropomorphism perceptions of the intelligent AGS in the dimension of closeness, mind perception, and social presence. Users in the control condition wouldn't see the anthropomorphic features and interact with solely text questions.

I, therefore, offer the following hypothesis:

Hypothesis 1 (H1). Users in the control condition will develop the lowest level of anthropomorphic perceptions compared with users in the other three conditions.

Persuasion knowledge includes beliefs about what the influence agent is attempting to achieve (persuasion motives), beliefs about how the agent tries to achieve it (persuasion tactics), and how do I deal with it (efficacy of coping) (Campbell and Kirmani 2000). Corresponding to each category, I propose perceived benevolence in the research model related to the perception of AGS being good in motives for users. I propose perceived neutrality to capture whether users believe AGS as being biased in the persuasion process. I also propose perceived control as the perception of efficacy to cope with persuasion attempts.

Users in the control or neutral conditions would be presented with system recommendations. However, intelligent agents will not persuade users to take their advice. Therefore, the system won't be biased toward certain options. In contrast, AGS in the persuasive and coercive conditions are more likely to be perceived as attempting to gain profit and benefit through intervention or persuasion, and as a result, the users tend to perceive the system as misleading or manipulative. Thus I propose, *Hypothesis 2 (H2). Users in the control or neutral condition will have a higher level of perceived neutrality compared with users in the other two conditions.*

Perceived benevolence has been identified as a core element of perceived trustworthiness in interpersonal relationships (Mayer et al. 1995b). It's "the extent to which a trustee is believed to want to do good to the trustor, aside from an egocentric profit motive"(Mayer et al. 1995b, p. 718). The intelligent AGS in the coercive condition tries to control users' decisions by acting as an authority and demanding or enforcing obedience. The intervention process performed by the coercive agents is likely to cause users to question the intention and goodwill of the system. Therefore, I hypothesize,

Hypothesis 3 (H3). Users in the coercive condition will have the lowest level of perceived benevolence compared with users in the other three conditions.

PKM posits that people typically use their persuasion knowledge not to resist a persuasion attempt but simply to maintain control over the outcome. Past research found that authoritative interventions tend to restrict interaction experience while facilitative interventions empower the message receiver (McCabe 2004). When coercive intelligent AGS intervene with users' decision-making by acting as an authority and challenging users' previous choices, it's likely to make users feel a loss of control. Therefore, I hypothesize,

Hypothesis 4 (H4). Users in the coercive condition will have the lowest level of perceived control compared with users in the other three conditions.

Users want to understand why and how a system makes its recommendations (Komiak & Benbasat, 2008; Wang & Benbasat, 2007). A higher-level perceived understanding of

AGSs can help users know better about the way AGSs work as well as be knowledgeable about the decision task at hand. In the persuasive and coercive conditions, the system would persuade and request users to change their decision to the same as the system advised and provide explanations. Explanations presented to users are a combination of "how" explanations and "why" explanations. To be more specific, after presenting the recommended option to users, intelligent AGS explains how she finds the recommended option for the user and why the option would be the best one for the user. The explanations may provide extra information such as past statistics as evidence to support persuasion. In this manner, the explanation facilities in the persuasive condition or the coercive condition can provide more related knowledge pertaining to the topic and enhance their understanding.

Therefore, I hypothesize,

Hypothesis 5 (H5). Users in the persuasive or the coercive will have a higher level of perceived understanding compared with users in the other two conditions.

4.2.3 Effect of Knowledge on Trust

According to PKM, people under persuasion attempt to develop their agent perception or knowledge to understand "the traits, competencies, and goals of the persuasion agent"(Friestad and Wright 1994, p. 3). Even though intelligent AGM are nonhuman entities, they can exhibit humanlike features and resemble human beings and feel like human beings. The effects of anthropomorphism on trust perception have received considerable interest from academics in recent years (for a review, see Glikson and

Woolley 2020). Anthropomorphism is believed to increase perceived similarity and decrease the psychological distance between users and systems, which leads to feelings of security and trust (Li and Sung 2021). There has been some research showing anthropomorphism increases feelings of trust in different situations (De Visser et al. 2016; Waytz et al. 2014).

I, therefore, offer the following hypotheses:

Hypothesis 6 (H6). Anthropomorphism perception will lead to emotional trust.

In the AGS context, a high level of perceived neutrality means that the user believes that intelligent AGS provide truthful and objective recommendations that are more likely to be a fit for them. For example, the explanation facilities may provide extra information to users such as two-sided reasoning and trade-off weighing and thus the users could be more assured that the system is not biased or inclined to pick one side. People holding such beliefs are also more likely to have stronger feelings of comfort and security to rely on the systems for advice. Therefore, I propose,

Hypothesis 7 (H7). Perceived neutrality will lead to emotional trust.

Emotional trust is supposed to be grounded in the attributions of motives for the influencing agent's behavior (McAllister 1995) and is closely related to the perception that he would act in the users' interest (Rempel et al. 1985). Perceived benevolence is regarding the good motives of the influencing agent. The more benevolent a user believes the influencing agent is, the more he will trust the agent emotionally. I, therefore, offer the following hypotheses:

Hypothesis 8 (H8). Perceived benevolence will lead to emotional trust.

When users' freedom of choice is threatened, their reactance tends to arouse. They will be more likely to resist and less likely to trust the persuader(Brehm and Brehm 2013). As suggested by Dietvorst et al. (2018) that giving people some control—even a slight amount—over an imperfect system can greatly remedy people's negative reactions. I posit that when users find systems are less restrictive and are granted more control, users will feel more comfortable taking advice from it since the decision is made by themselves rather than by coercion. I thus propose,

Hypothesis 9 (H9). Perceived control will lead to emotional trust.

When users question the motivation of the influencing agent, they may elicit more persuasion knowledge (Friestad and Wright, 1994), which also results in greater cognitive elaboration on the topic of interest (Campbell and Kirmani, 2000). If the advice provider is deemed to be benevolent, people tend to be more confident in the accuracy of advice and find the advice provider competent (Barnett White 2005). Thus,

Hypothesis 10 (H10). Perceived benevolence will lead to cognitive trust.

When users believe the intelligent AGS is unbiased and provide truthful recommendations, they are more likely to believe that the advice it generates is objective and sound and therefore a good option for them. As a result, users are also more likely to find the system competent in performing decision tasks. Therefore, I propose,

Hypothesis 11 (H11). Perceived neutrality will lead to cognitive trust.

A high level of perceived control means that the user believes that intelligent AGS is granting users control over the final decision. It's not manipulative and thus more reliable.

It is more likely to act for the users and choose the most appropriate option, and thus more competent in the decision tasks. Therefore, I propose,

Hypothesis 12 (H12). Perceived control will lead to cognitive trust.

Based on PKM, topic knowledge facilitates comprehension of the message content and can be useful in examining the arguments made by the persuading agent. Users are inclined to understand why and how a system makes its recommendations (Wang and Benbasat 2007; Zhao et al. 2019), even for intelligent systems that may sometimes be inscrutable (Rai 2020). Research found that higher levels of perceived understanding of AGSs will make the advice more justifiable and reasonable, which makes users believe systems as competent in offering advice (Diakopoulos and Koliska 2017). I, therefore, propose:

Hypothesis 13 (H13). Perceived understanding will lead to cognitive trust.

4.2.4 Trust and Reuse Intentions

To examine users' reuse intention of intelligent agents, I differentiate two types of use intentions: intention to delate and intention to let it assist. Both intentions are to use the intelligent agent again to support his or her decision-making. They differ in the extent of dependence on intelligent AGS. When users intend to delegate a decision, they accept the advice without scrutinizing it. When users intend to reuse the system as an assistant, they plan to thoroughly go over the options and make the final decision by themselves. Emotional trust is seen as more special and less superficial than cognitive trust (Johnson-George and Swap 1982). It was characterized by a greater investment of time and emotion

(Rempel et al. 1985). Customers are more likely to intend to delegate their future decision to an intelligent AGS if they develop a high level of emotional trust toward it. Therefore,

Hypothesis 14 (H14). Emotional trust will lead to reuse intentions to delegate.

In contrast, cognitive trust is more situation-specific. It's a rational assessment of the intelligent agent's competency in performing the task at hand. Users are more independent decision-makers and invest cognitive efforts to understand related content. The former mental investment would make it harder to automate future decisions thus more likely to adopt an assistantship relationship and use the system as a decision aid in the future. Therefore, I propose,

Hypothesis 15 (H15). Cognitive trust will lead to reuse intentions to let it assist.

4.2.5 Relationship between Different Types of Trust

Behavioral trust was conceptualized as “situationally activated cognitive and emotional trust”(Lewis and Weigert 1985, p. 977). In the advice-giving context, behavioral trust has been measured as the adoption or utilization of algorithmic advice (e.g. Bonaccio and Dalal 2006). I argue that the more users believe that intelligent AGS has the competency in providing good advice, the more likely they are going to take the advice from them. Moreover, users’ feeling of security to rely on AGSs can effectively enhance their acceptance of advice generated by AGS. Thus,

Hypothesis 16 (H16). Emotional trust will lead to behavioral trust.

Hypothesis 17 (H17). Cognitive trust will lead to behavioral trust.

4.2.6 User Characteristics as Moderators

Trust Propensity

Propensity to trust is the general tendency and willingness of one person to trust another person (Mayer et al. 1995b). People low in trust propensity are less inclined to form initial trust toward others. However, once they develop feelings of security with the influencing agent, they are more likely to cherish and rely on this emotional trust. They place a higher weight on emotional trust compared with people high in trust propensity and let the trust perceptions guide their behaviors. Thus I propose,

Hypothesis 18 (H18). The relationship between emotional trust and behavioral trust will be strengthened when users possess a low trust propensity.

Topic Expertise

Topic expertise is how much one knows about the topic of persuasion. People lacking expertise in a specific domain tend to rely on experts in the field. In this sense, when someone without topic expertise believes that the intelligent agent has the competence and expertise to perform well in decision making, he or she is more likely to adopt the advice from the intelligent agent. In another word, once people without expertise develop cognitive trust, this cognitive trust is more predictive of their trusting behaviors. Therefore, I propose,

Hypothesis 19 (H19). The relationship between cognitive trust and behavioral trust will be strengthened when users possess low topic expertise.

CHAPTER 5: METHOD

5.1 Study Procedure

I conducted an online experiment to test the proposed research model. Qualtrics was employed to set up the experiment platform.

During the experiment, participants need to provide their consent to participate first. They were then asked to imagine themselves in a certain task situation (see appendix for details). The scenario was that they were relocated to a new place and were planning to rent a place. The landlord of the place required each person in the family to be covered by renters insurance so the task was to choose a renters insurance plan for the family. Participants were presented with five plans plan A to plan E which all can meet the requirements of the landlord. They need to look through the plan and make an initial decision on which plan to choose.

The renter insurance plans were designed according to the real Geico Renters Insurance online quote system in the task scenario. The five plans range from $200 per year to $229 per year. The price difference is minimal, but each plan differs in its coverage categories. For example, Plan B would double the coverage for personal property damage or loss as Plan A while Plan A has the highest personal liability limit. In other words, there were trade-offs to be decided when choosing a plan and there was no optimal solution in the given scenario. For participants unfamiliar with renters insurance plans, they can see explanations of each terminology. They were notified to hover the mouse over the coverage categories to receive more information about that particular coverage option. For example, when hovering over “Personal Property Coverage”, the system would show “Coverage you need to replace all your personal property (e.g. furniture, electronics, and clothing) if lost, damaged, or destroyed” as the explanation.

After making their initial decision, participants were introduced to an intelligent agent (or a new type of system in the control condition) that asks for user input and collects information from users. The questions include basic information about the place to rent (e.g. type of the property, living size of the place, age of the property, zip code of the place), and information regarding users themselves (e.g demographic information such as age, gender and previous experience with renters insurance). The intelligent agent will extract information from participants’ answers and compose “personal” persuasive messages that cater to their situation. For example, an intelligent agent persuades “For people at your income level, the value of your belongings can quickly add up, so you'll want to make sure you are covered appropriately.”

After finishing all the interaction questions, the intelligent agent presents the recommended option to the user and asks him/her to make the decision for the second time. If a user chooses an option different from what the intelligent agent recommended, the intelligent agent will intervene and persuade the user to change his decision to the system recommendation. I measure users' behavioral trust (weight on advice) based on how much users change their decisions according to what intelligent AGS recommends. Participants are subsequently asked to rate their perceptions of the AGS they just use.

To increase the perceived human likeness of the system, I create an advisor using a woman avatar and give her a human name Ana (Logg et al. 2019). Animaker was adopted to create the animations of avatars to represent the virtual agent Ana of the system. She can show facial expressions such as smiling and thinking or angry and disappointed in the persuasive and coercive conditions. I also set her up to provide emotionally expressive responses (Novikova 2016). For instance, the intelligent agent would show understanding of hard work, express gratefulness, and encourages participants to go on when participants approach the end of the questions. She also exhibits extrovert interactions such as introducing herself actively and asking the name of the participants, calling the participants by their names and making friends with them (Moshkina 2011).

The flow chart (Figure 9 Flow Chart of Experiment) below outlines the process of the experiments.

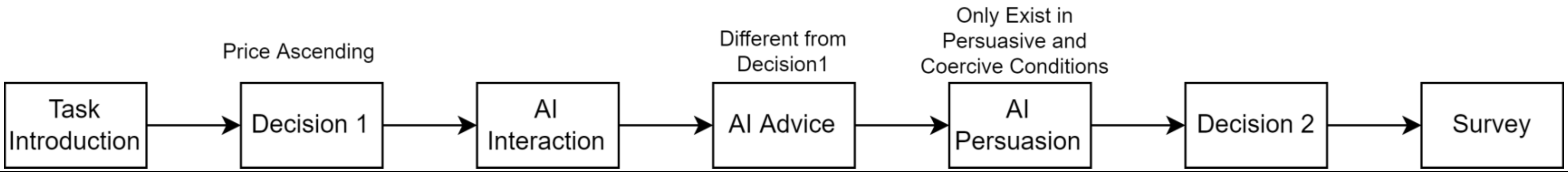


Figure 9 Flow Chart of Experiment

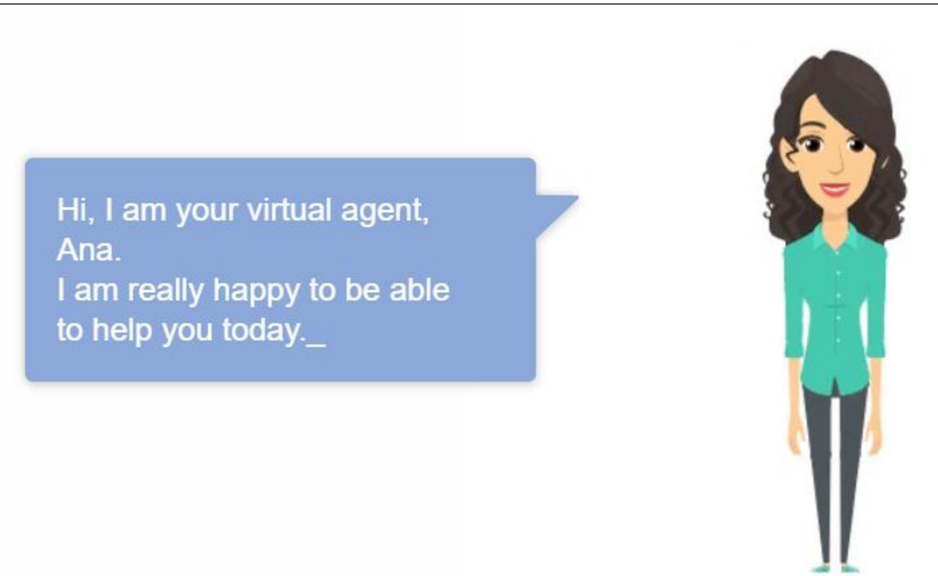
Agent Presentation (Control Condition)	Agent Presentation (Neutral Condition)
	

Figure 10 Representation of Intelligent Virtual Agent

5.2 Measurement

I develop the measures based on prior literature and adapt them to the current research context. All measures are based on five-point Likert scales. Items for anthropomorphism were adapted from Lee et al. (2006); items for perceived benevolence were adapted from Wang and Benbasat (2005) and items for perceived neutrality were adapted from Wang et al. 2018; items for perceived control were adapted from Lee and Benbasat (2011); items for perceived understanding were adapted from Wang and Benbasat (2016); items for the cognitive trust were adapted from Wang and Benbasat (2016); items for emotional trust and reuse intention were adapted from Komlak and Benbasat (2006). See Table 3 for details.

Table 3 Construct Items, References, and Descriptive Statistics			
Name	Item based on 5-point Likert (Strongly disagree - Somewhat disagree - Neither agree nor disagree - Somewhat agree - Strongly agree)	Mean	Std. Dev.
Anthropomorphism (adapted from Lee et al. 2020) Sub-constructs: Mind Perception; Closeness; Social Presence			
Anthropomorphism - Closeness Regarding the virtual advisor, I feel			
AC1	emotionally close to her.	3.131	1.371
AC2	I made a friend of her.	3.145	1.402
AC3	I wanted to have a conversation with her.	3.249	1.440
Anthropomorphism - Mind Perception I feel that the virtual advisor			
AMP1	was able to think by herself.	3.733	1.182
AMP2	behaved of her own will.	3.676	1.252
AMP3	was conscious during interactions with me.	3.681	1.271
Anthropomorphism – Co-presence			

Using the virtual advisor,			
ACP1	I had the sense of being together with a real advisor.	3.459	1.358
ACP2	I felt co-located with a real advisor.	3.430	1.366
ACP3	I felt that she and I were together in the same place.	3.419	1.367
ACP4	I felt that I had face-to-face communication with a real advisor.	3.317	1.450
Perceived Neutrality (adapted from Wang et al. 2018) I believe the virtual advisor			
PN1	to be biased toward certain renters insurance plan.	3.045	1.356
PN2	provided a misleading recommendation.	2.699	1.410
PN3	distorted factors in favor of certain renters insurance plan when giving a recommendation.	2.814	1.415
Perceived Benevolence (adapted from Wang and Benbasat 2005) I believe that the virtual advisor			
PB1	puts my interest first.	3.821	1.144
PB2	keeps my interests in its mind.	3.912	1.120
PB3	wants to understand my needs and preferences.	3.910	1.175
Perceived Control (adapted from Lee and Benbasat 2011) When choosing a renters insurance plan,			
PC1	I felt I was in control.	3.826	1.134
PC2	I think that I had a lot of control over the plan selecting process.	3.910	1.088
PC3	The way I was asked by the virtual advisor made me feel I was in control.	3.771	1.139
Perceived Understanding (adapted from Wang and Benbasat 2016) About the virtual advisor, I believe that			
PU1	I could easily understand her reasoning process.	4.100	1.140
PU2	she made her reasoning process clear to me.	4.011	1.209

PU3	it was readily apparent to me how she generates her recommendation.	3.792	1.257
PU4	her logic in providing advice was clear to me.	3.930	1.230
PU5	I could understand why and how she recommends the renters insurance plan to me.	3.937	1.236
Emotional Trust (Adapted from Komiak and Benbasat 2006) About the virtual advisor,			
ET1	I feel safe about relying on her for my prediction decision.	3.713	1.203
ET2	I feel comfortable about relying on her for my decision.	3.783	1.217
ET3	I feel content about relying on her for my decision.	3.783	1.193
Cognitive Trust (adapted from Wang and Benbasat 2016) About the virtual advisor, I believe			
CT1	she is competent and effective in providing me with a recommendation.	3.900	1.039
CT2	she performs her role of giving me a recommendation very well.	3.939	1.081
CT3	she is a capable and proficient provider of renters insurance plans overall.	3.878	1.102
CT4	she is very knowledgeable about renters insurance plans in general.	3.968	1.079
Reuse Intention (adapted from Komlak and Benbasat 2006) Sub-constructs: Intention to Delegate; Intention to Let Assist			
Reuse Intention (Delegate) About the virtual advisor, I am willing to			
RID1	delegate to her for my decision about which renters insurance plan to buy.	3.500	1.317
RID2	let her decide which renters insurance plan to choose on my behalf.	3.414	1.375
RID3	give her my authorization to choose renters insurance for me.	3.333	1.405

Reuse Intention (Assist) About the virtual advisor, I am willing to			
RIA1	use her as an aid to help with my decision about which renters insurance plan to buy.	3.925	1.063
RIA2	let her assist me in deciding which renters insurance plan to buy.	3.962	1.088
RIA3	use her as a tool that suggests to me a renters insurance plan that I can choose.	3.980	1.033
Topic Expertise (adapted from Wang and Benbasat 2009; Xiao and Benbasat 2018)			
PE1	I am knowledgeable about renters insurance plans.	3.466	1.340
PE2	Choosing a renters insurance option fall under my domain expertise.	3.265	1.387
PE3	Among my circle of friends, Im one of the experts on renters insurance.	3.011	1.472
Trust Propensity (adapted from Wang and Benbasat 2007)			
TP1	I generally trust other people.	3.455	1.263
TP2	I tend to count upon other people.	3.312	1.280
TP3	I generally have faith in humanity.	3.676	1.163
Organizational Commitment (Common Method Bias Question; adapted from Ahuja et al. 2007) About my current work organization or the last place I worked (if you're a student, think of the school where you study),			
CMB1	I am willing to put in a great deal of effort, beyond what is normally expected, in order to help my organization be successful.	4.122	0.989
CMB2	I really care about the fate of my organization.	4.124	0.990
CMB3	For me, my organization is the best of all possible organizations for which to work.	3.905	1.137

CHAPTER 6: DATA ANALYSIS AND RESULTS

6.1 Characteristics of the Sample

Participants for the pilot study were recruited from Amazon Turk. Participants need to be older than 18 years and live in the United States. I conducted five rounds of data collection in the pilot to revise the instruments in the survey and adjust the features of the system in each condition. A total of 142 participants attended the pilot study. The official data collection was conducted through a reputable marketing panel company in the United States. A total of 442 valid responses were included in the final data analysis.

The sample of the experiment comprised a diverse population. Around 58% of female participants finished the experiment. Participants are from different age groups (18 and up) and the percentages in each group are balanced out. In regards to education, more than half of the sample have a university degree or higher. Around 55% of the participants have a yearly income of less than $47,000, which is close to the real median personal income in the US in 2021. See Table 4 for a summary and Figure 11 for an illustration.

Table 4 Characteristics of the Sample

Demographic Variables	**Distribution**
Gender	Female: 57.69%; Male: 41.63%; Gender not listed here: 0.23%; Prefer not to answer: 0.45%
Age	18 – 24: 12.22%; 25 – 34: 23.08%; 35 – 44:16.74%; 45 – 54: 11.31%; 55 – 64: 8.37%; 65 – 74: 18.78%; 75 or older: 9.50%
Education	Less than high school: 1.36%; High school graduate: 32.81%; Diploma/Sub-degree: 13.80%; University degree: 35.07%; Post-graduate degree: 16.97%
Income	$0 - $26,000: 27.60%; $26,001 - $47,000: 27.83%; $47,001 - $70,000: 21.95%; $70,001 - $100,000: 12.22%; $100,000 and above: 10.41%

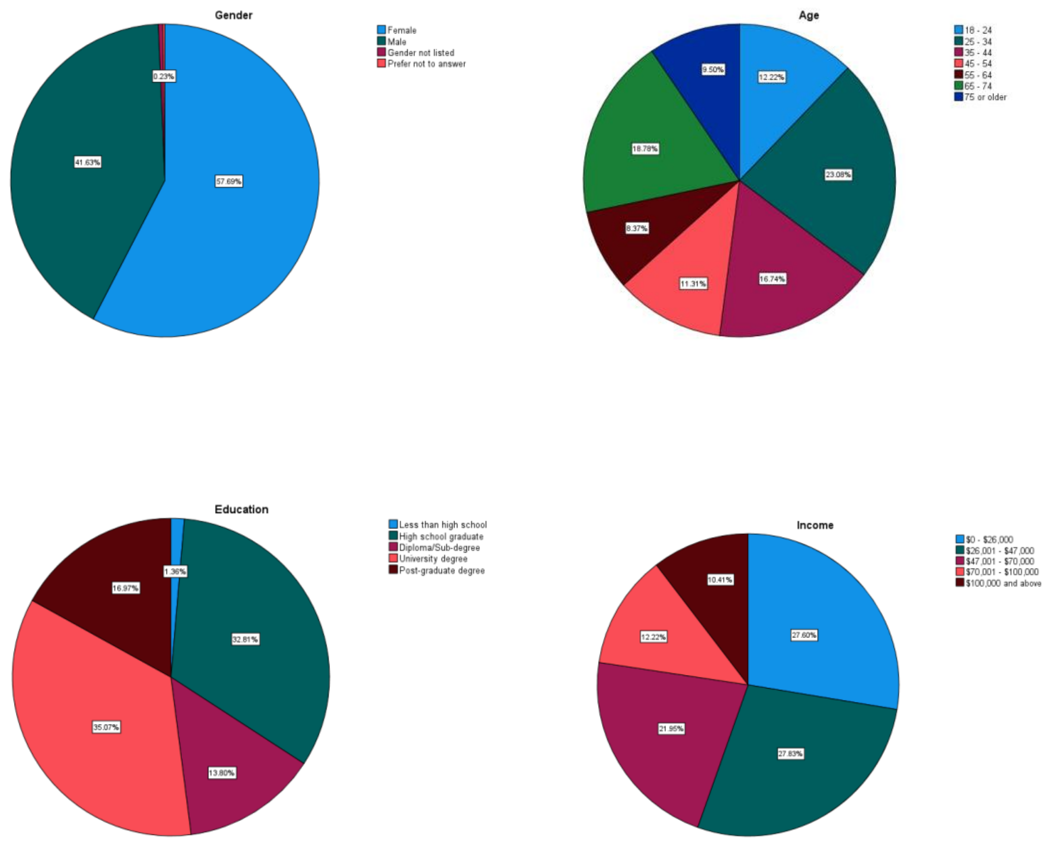


Figure 11 Characteristics of the Sample

6.2 Main Model

In the main model, I test the effects of users' knowledge levels in each category on trust and eventually their reuse intentions. Hypothesis 6 to Hypothesis 15 are tested in the main model. I used two ways to analyze the model. First, I analyzed the main model using covariance-based structural equation modeling using R4.2.0 (R Core Team 2022) and the Lavaan package (Rosseel 2012). I analyzed the measurement model first and then the full structural equation model combining the sub-constructs. In the meanwhile, I used the software ADANCO 2.0 Professional for Windows (Dijkstra and Henseler 2015) to calibrate and test the composite measurement models.

6.2.1 Measurement Model

The model fit indices for the measurement model (fitted using Lavaan 4.2.0) are within the recommended ranges (Tomarken and Waller 2005). The CFI is above 0.9, and both RMSEA and SRMR are below 0.08, indicating a good fit for the model. See Table 6 for details. Moreover, all constructs demonstrated (1) high internal consistency reliability, with Cronbach's alpha ranging from 0.882 to 0.955, well above the recommended 0.7 threshold (Fornell and Larcker 1981); (2) good discriminant validity in that inter-construct correlations don’t exceed the square root of the AVEs of each construct; (3) good convergent validity in that all items have good loadings on the latent construct and the AVE for all constructs exceeds 0.5.

Table 5 Measurement Model Statistics

	#of Items	CFA Item Loadings^	Cronbach's alpha(α)	AVE	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1. Anthropomorphism	10	0.854 - 0.960	0.955	0.712	**0.844**							
2. Perceived Neutrality	3	0.822 - 0.949	0.921	0.803	0.116	**0.896**						
3. Perceived Benevolence	3	0.892 - 0.934	0.939	0.891	0.770	-0.102	**0.944**					
4. Control	3	0.834 - 0.863	0.882	0.809	0.601	0.026	0.608	**0.899**				
5. Perceived Understanding	5	0.832 - 0.927	0.947	0.826	0.653	-0.052	0.684	0.544	**0.909**			
6. Emotional Trust	3	0.916 - 0.947	0.950	0.909	0.770	-0.065	0.809	0.632	0.681	**0.953**		
7. Cognitive Trust	4	0.878 - 0.913	0.943	0.854	0.739	-0.073	0.788	0.614	0.671	0.852	**0.924**	
8. Reuse Intention	6	0.885 - 0.940	0.928	0.735	0.758	-0.012	0.747	0.563	0.631	0.825	0.853	**0.857**

^The CFA loadings are the range of loadings from the lowest to the highest on each latent construct.

Bolded diagonal elements represent the square root of the AVE.

6.2.2 Structural Model

The fit statistics (Table 6) suggest that the structural model demonstrates an acceptable fit with the data.

Table 6. Model Fit Statistics

	Measurement Model (n = 442)	Measurement Model with Common Method Factor (n = 442)	Structural Model by Subconstructs (n = 442)
CFI	0.964	0.961	0.954
Chi-square/df	1195/ 539	1370/ 636	1404/ 558
RMSEA	0.052	0.051	0.059
SRMR	0.028	0.034	0.043

Common Method Variance

To evaluate common method variance (CMV), I included a latent common method factor "organizational commitment" in the survey and put it in the confirmatory factor analysis (CFA) (Podsakoff 2003). To assess whether common method bias exists, I compared the fit indices with the original CFA model (Table 5 Measurement Model Statistics). The change in the CFI value is 0.003, which is lower than the preferable threshold of 0.05 (Little 1997).

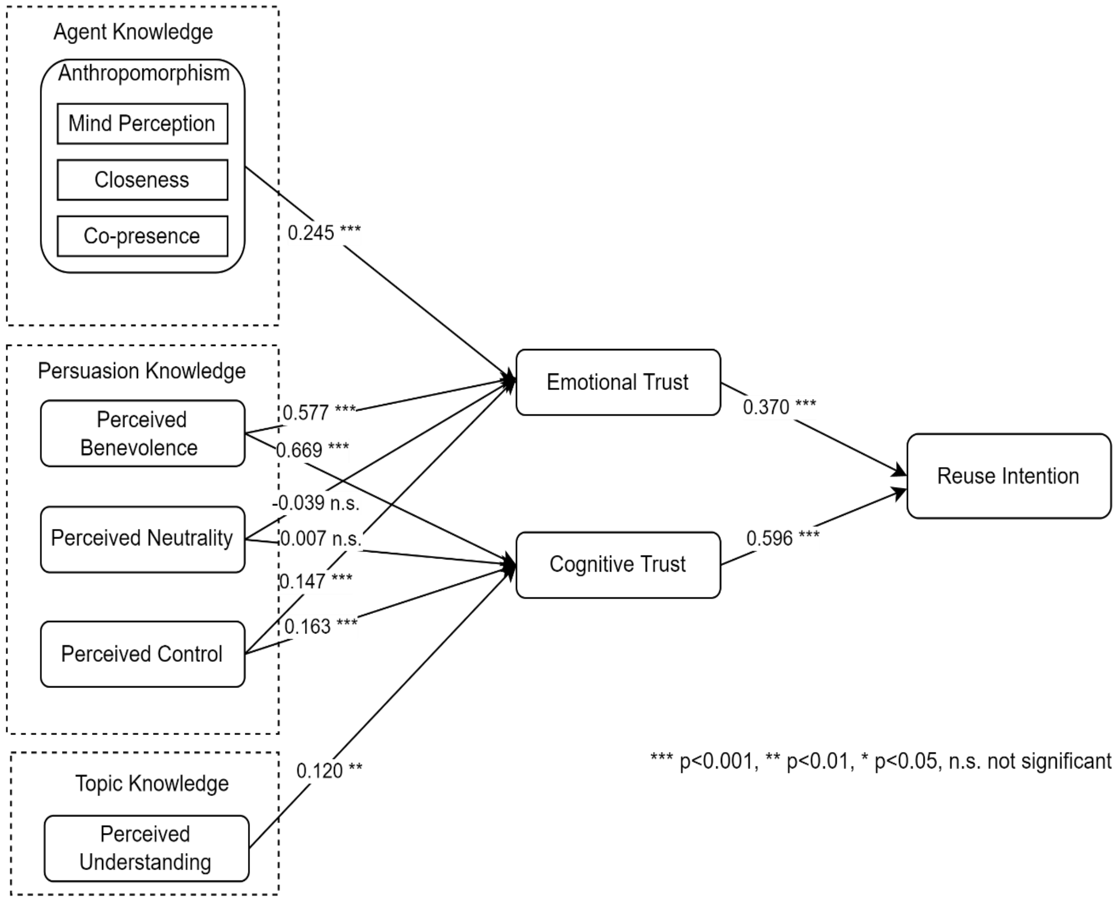


Figure 12 Structure Model Results by LAVAAN

Figure 12 shows the standardized path coefficients and the significance level of the structural model. Anthropomorphism, perceived benevolence, and perceived control were tested to be significant antecedents of emotional trust. Perceived understanding, perceived benevolence, and perceived control were tested to be significant antecedents of cognitive trust. Both emotional trust and cognitive trust lead to reuse intention.

To explore the effects of sub-dimensions of anthropomorphism and sub-dimensions of reuse intention, I ran a structural model with all the subconstructs. The results were presented in Figure 13 below. Only the subconstruct Co-presence can significantly lead to emotional trust. In terms of reuse intention, both types of trust can significantly lead to intention to delegate decisions to AGS or intention to use AGS as assistants.

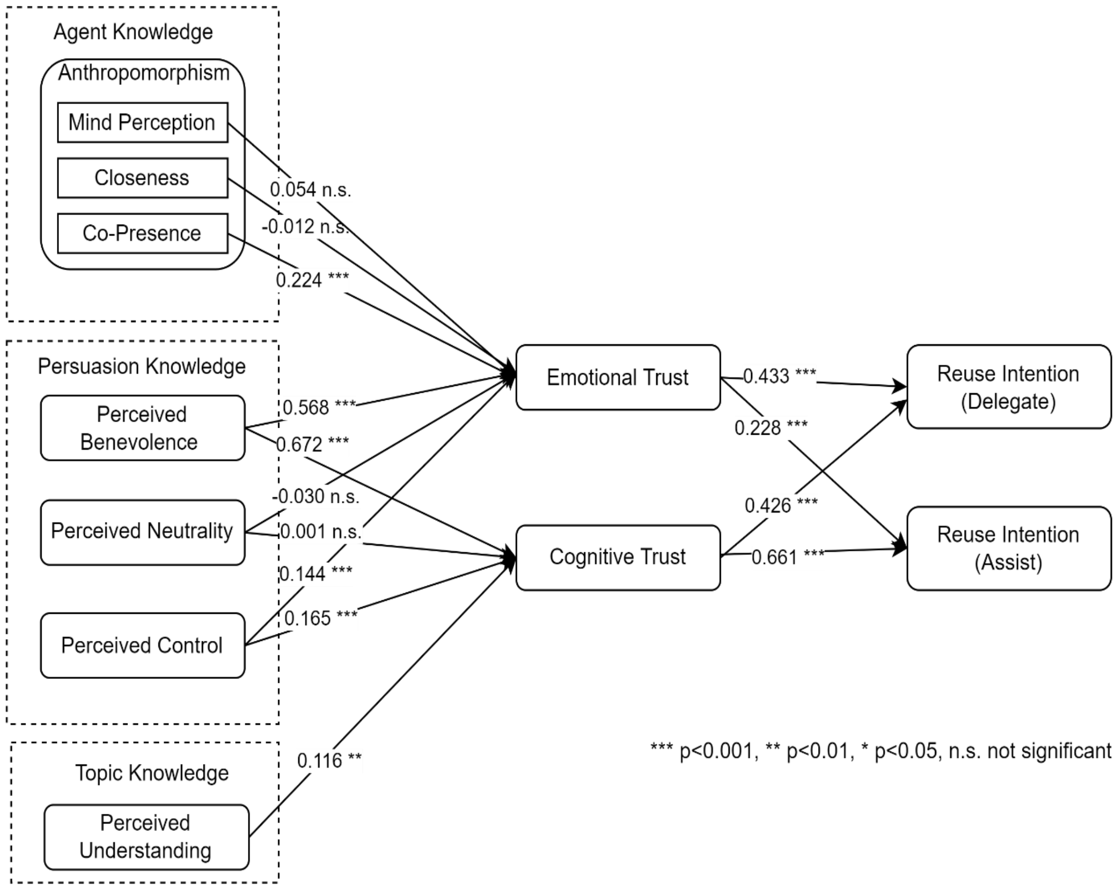


Figure 13 Structure Model (Subconstruct) Results by LAVAAN

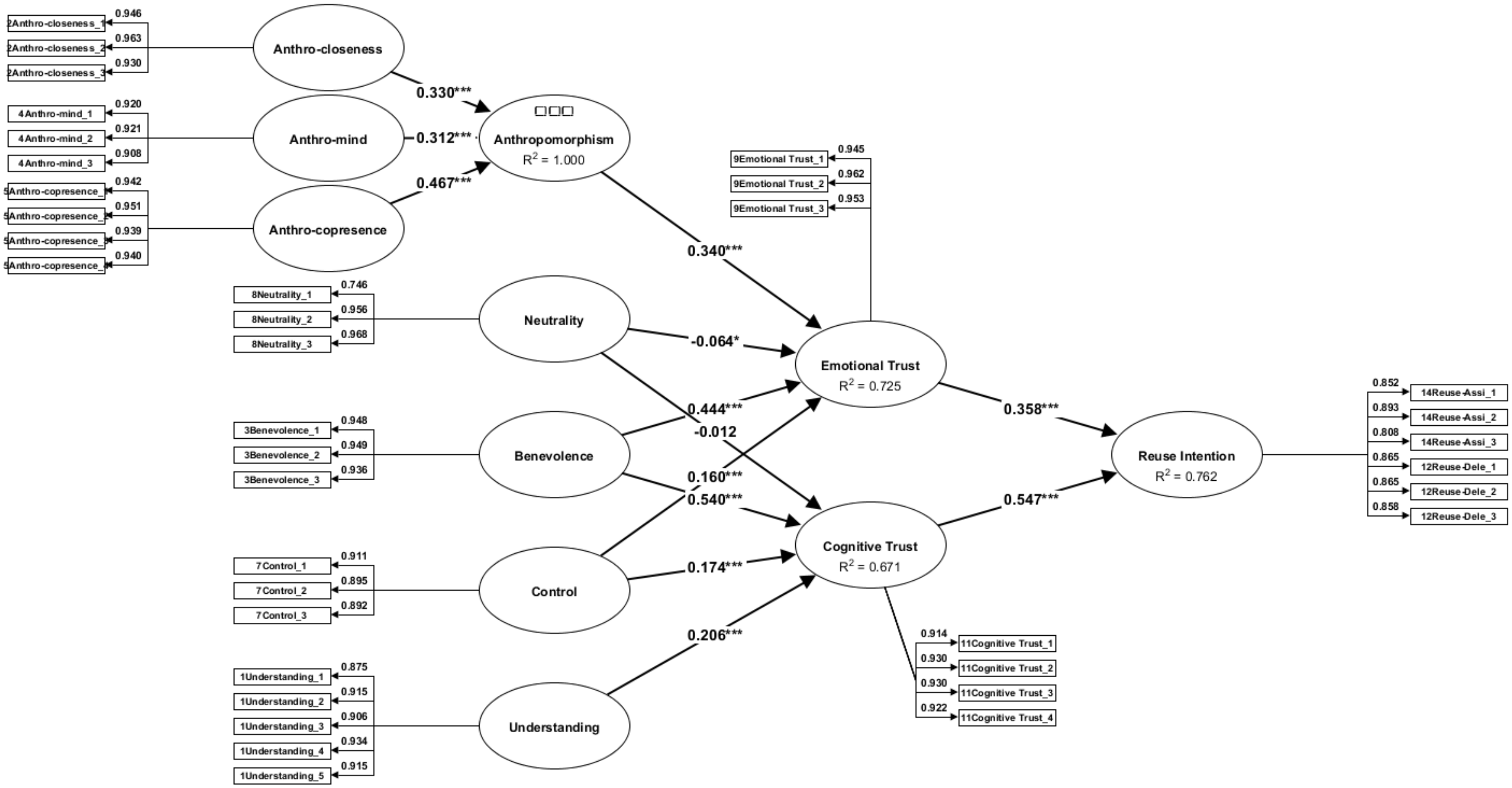


Figure 14 Results of the Main Research Model by Adanco

Table 7 Results of Hypothesis Test by Adanco			
Tested Hypothesis/Path	**β**	**t-statistic**	**Supported?**
H6. Anthropomorphism → Emotional Trust	0.3397	5.8141 ***	Yes
H7. Neutrality → Emotional Trust	-0.0636	-2.1247 *	Yes
H8. Benevolence → Emotional Trust	0.4437	7.6002 ***	Yes
H9. Control → Emotional Trust	0.1596	3.3181 ***	Yes
H10. Neutrality → Cognitive Trust	-0.0117	-0.3833 (n/s)	No
H11. Benevolence → Cognitive Trust	0.5397	11.3669 ***	Yes
H12. Control → Cognitive Trust	0.1739	3.9486 ***	Yes
H13. Understanding → Cognitive Trust	0.2063	4.0607 ***	Yes
H14. Emotional Trust → Reuse Intention	0.3583	5.4688 ***	Yes
H15. Cognitive Trust → Reuse Intention	0.5475	8.1298 ***	Yes

Notes: ***p < 0.001; **p < 0.01; *p < 0.05, n/s = not significant.

Table 8 R-Squared Statistics		
Construct	Coefficient of determination (R^2)	Adjusted R^2
Emotional Trust	0.7252	0.7227
Cognitive Trust	0.6711	0.6681
Reuse Intention	0.7622	0.7611

I also conducted Partial Least Squares regression (PLS) using ADANCO 2. The results of the structural model tests are visually presented in Figure 14 and summarized in Table 7 and Table 8. We can see that nine out of the ten hypotheses are supported. The R square indices are also preferable indicating a large percentage of variations can be explained by the model.

6.2.3 Mediation Analysis

In the research model, I proposed that different knowledge levels (agent knowledge, persuasion knowledge, and topic knowledge) during persuasion lead to trust and eventually reuse intentions. Therefore, two types of trust (emotional trust and cognitive trust) are expected to mediate the relationship between knowledge levels and reuse intentions. Mediation analysis was conducted in Lavaan to explore emotional trust and cognitive trust as mediators. See Table 9 for results. Mediation tests using ADANCO can be found in the Appendix.

Table 9 Tests of Mediation

Path	Direct Effect	t-value	Indirect Effect	t-value	Type of Mediation Relationship
Anthropomorphism → Emotional Trust → Reuse Intention	0.266	4.596***	0.083	3.350**	Partial (complementary mediation)
Neutrality → Emotional Trust → Reuse Intention	0.043	1.525(n/s)	-0.015	-1.429(n/s)	None (no effect)
Benevolence → Emotional Trust → Reuse Intention	-0.137	-1.522(n/s)	0.207	4.631***	Full (indirect only)
Control → Emotional Trust → Reuse Intention	-0.122	-2.865**	0.055	3.116**	Partial (complementary mediation)
Neutrality → Cognitive Trust → Reuse Intention	0.043	1.525(n/s)	-0.002	-0.124(n/s)	None (no effect)
Benevolence → Cognitive Trust → Reuse Intention	-0.137	-1.522(n/s)	0.404	7.570***	Full (indirect only)

Control → Cognitive Trust → Reuse Intention	-0.122	-2.865**	0.105	3.685***	Partial (complementary mediation)
Understanding → Cognitive Trust → Reuse Intention	-0.014	-0.339(n/s)	0.072	2.624**	Full (indirect only)

Notes: ***p < 0.001; **p < 0.01; *p < 0.05, n/s = not significant

I found that anthropomorphism's effect on reuse intention is partially mediated by emotional trust. The effect of perceived control on reuse intention was also partially mediated by emotional trust. Similarly, the effect of perceived control on reuse intention was partially mediated by cognitive trust. Moreover, both emotional trust and cognitive trust served as full mediators between perceived benevolence and reuse intentions. The relationship between perceived understanding and reuse intention was fully mediated by cognitive trust. Neutrality had no direct effect or mediation effect on reuse intention.

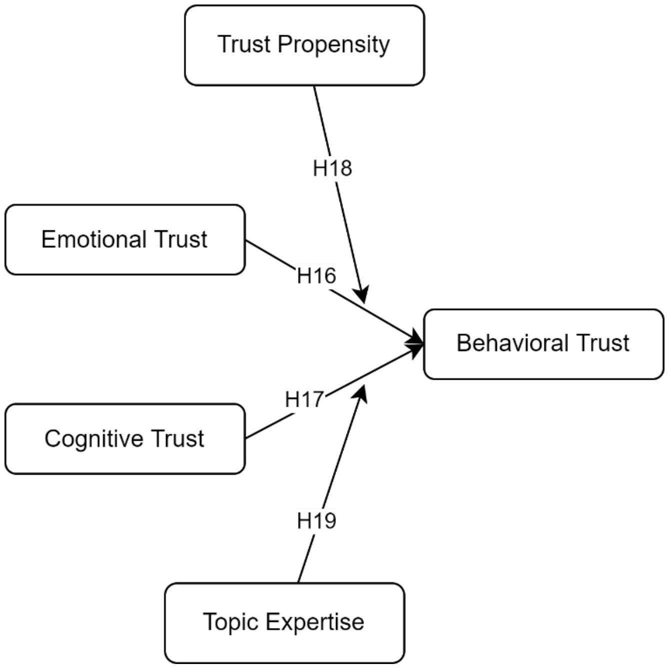


Figure 15 Model of Behavioral Trust on Emotional Trust and Cognitive Trust

6.3 Behavioral Trust

Behavioral trust is defined as the acceptance of advice from intelligent advice-giving systems. It is coded as 1 (final decision same as system recommendation) and 0 (final decision different from system recommendation). Logistic regression was conducted to examine whether emotional trust and cognitive trust as significant predictors of behavioral trust. See Figure 15 for an illustration.

I found that only putting emotional trust and cognitive trust as the independent variables to behavioral trust didn't make them significant predictors. The p-value of emotional trust is 0.093 and the p-value of cognitive trust is 0.203. However, when I put trust propensity and topic expertise as moderators in the model, emotional trust can significantly predict behavioral trust ($\beta = 0.638$, $p<0.01$). Cognitive trust also became a significant predictor of behavioral trust ($\beta = 0.490$, $p<0.05$). In the meanwhile, the two interaction effects were also significant. Trust propensity moderated the relationship between emotional trust and behavioral trust (β = -0.065, p<0.05). For people less prone to trust others, the built-up emotional trust is more likely to lead to behavioral trust. Similarly, topic expertise moderated the relationship between cognitive trust and behavioral trust (β = -0.056, p<0.05), which indicates that cognitive trust has more impact on behavior trust for those who have less expertise about the topic. See Table 10 for a summary of the results.

Table 10 Results of Hypothesis Test of Behavioral Trust

Tested Hypothesis/Path	β	t-statistic	Supported?
H16. Emotional Trust → Behavioral Trust	0.638	8.878 **	Yes
H17. Cognitive Trust → Behavioral Trust	0.490	4.919 *	Yes
H18. Emotional Trust * Trust Propensity → Behavioral Trust	-0.065	4.458 *	Yes
H19. Cognitive Trust * Topic Expertise → Behavioral Trust	-0.056	4.855 *	Yes

Notes: ***p < 0.001; **p < 0.01; *p < 0.05, n/s = not significant.

6.4 Knowledge Levels by Experimental Conditions

In this section, I tested the first five hypotheses. I look into whether experiment conditions that have various design features lead to different levels of knowledge in each category.

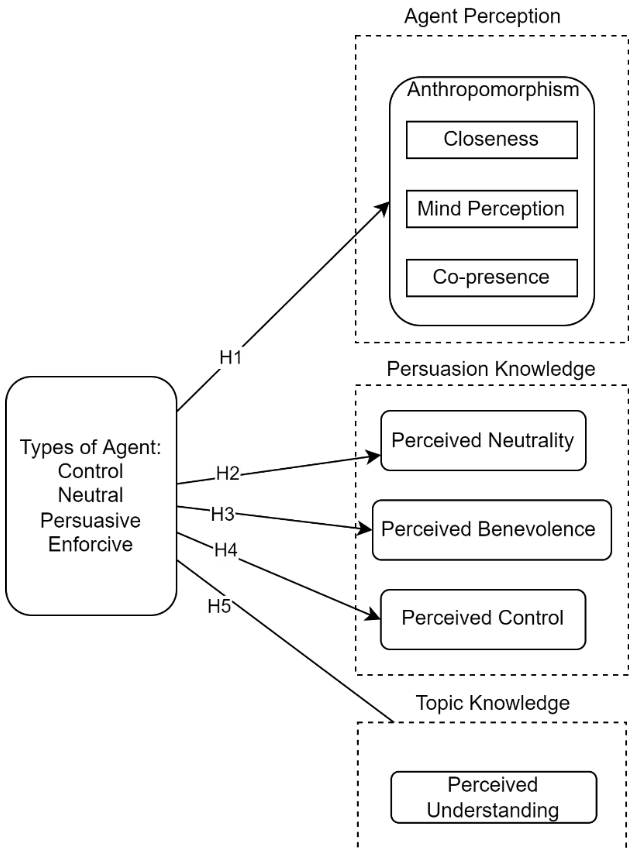


Figure 16 Model of Experimental Conditions on Knowledge

6.4.1 Anthropomorphism Levels by Experimental Conditions

Compared with the control condition without avatar animations, the other three conditions all have higher averages of anthropomorphism perception. See Figure 17 below. Anthropomorphism has an average of 3.252 in the control condition, 3.530 in the neutral condition, 3.506 in the persuasive condition, and 3.385 in the coercive condition. It’s not significantly different though (f=1.345. p=0.259).

To find out the reason behind this, I look into each subconstructs of anthropomorphism (Closeness, Mind Perception, and Co-presence). The patterns are consistent across subcontracts of anthropomorphism that the control conditions all have the lowest averages among the four conditions. The difference is that the coercive condition didn't perform well in the aspect of closeness and co-presence while it still creates a high sense of mind perception, implying that users still believe a coercive intelligent agent can think like a human being.

I conducted a contrast ANOVA with coefficients of “0.9 -0.3 -0.3 -0.3” to compare the control condition with the other three conditions in the mind perception dimension. The result is significant ($t= -1.977$, $p < 0.05$). In this sense, participants in the control condition without seeing the animated avatar presentation were significantly less likely to think of the intelligent agent as being able to think compared with the other three conditions with animated avatars. The results of contrast analysis with the other two sub-dimensions (closeness and copresence) were not significant. Therefore, H1 is partially supported.

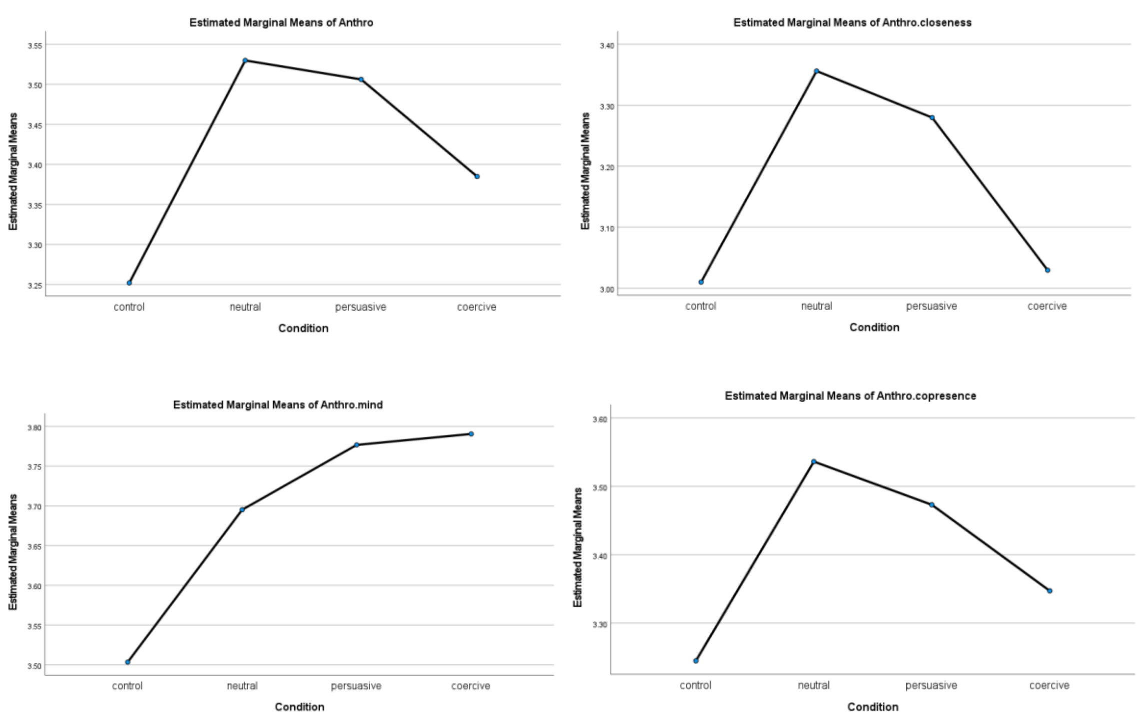


Figure 17 Anthropomorphism by Experimental Conditions

6.4.2 Perceived Neutrality by Experimental Conditions

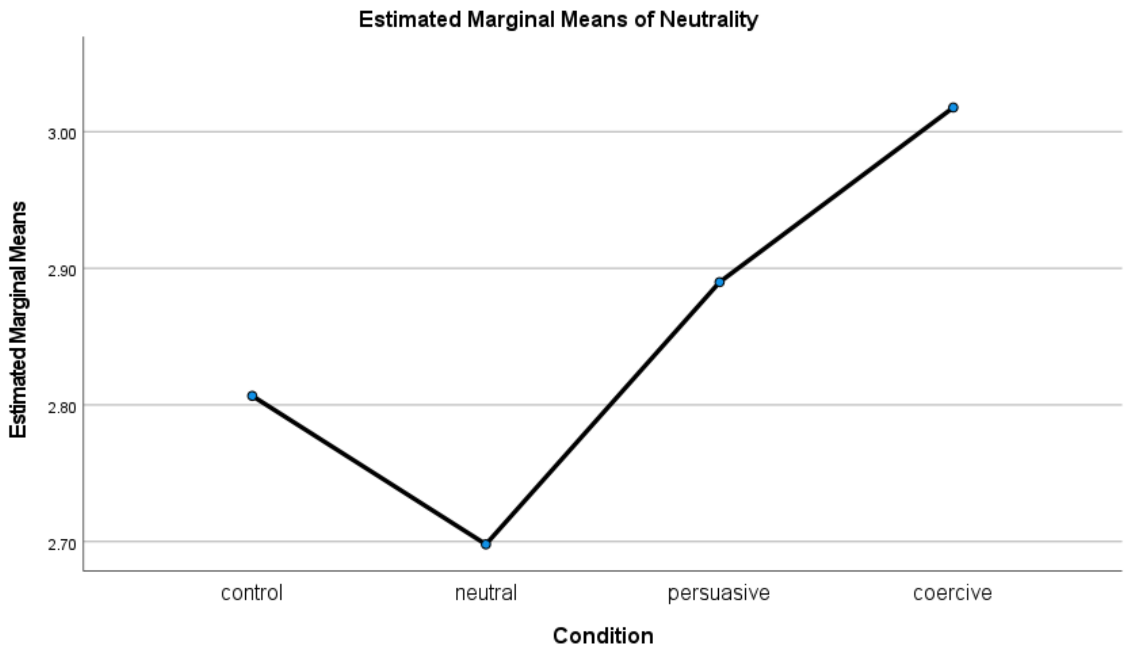


Figure 18 Perceived Neutrality by Experimental Conditions

Among the four conditions, control and neutral condition have lower averages of perceived neutrality. ANOVA test between four conditions was not significant (f = 1.241). I did ANOVA contrast analysis with coefficients of "0.5 0.5 -0.5 -0.5" to compare the control and the neutral condition with the other two conditions and the results were not significant (t = -1.646). Therefore, H2 is not supported.

6.4.3 Perceived Benevolence by Experimental Conditions

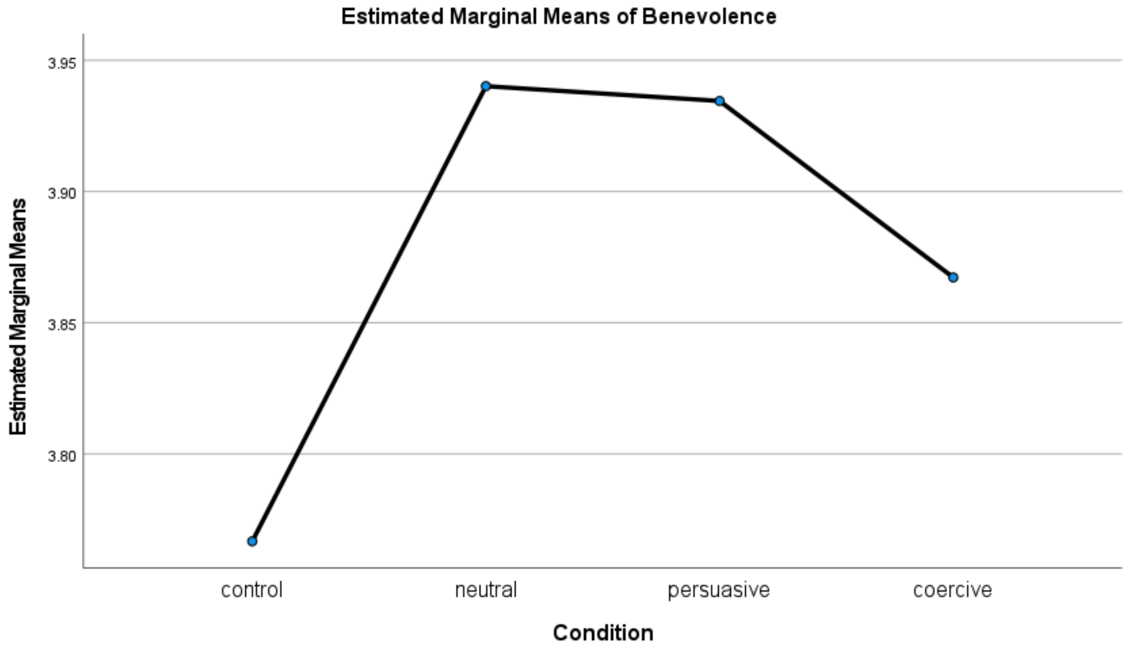


Figure 19 Perceived Benevolence by Experimental Conditions

Among the four conditions, control has the lowest average of perceived benevolence (M = 3.767, SD = 1.024). Participants in the coercive condition had lower perceived benevolence (M = 3.867, SD = 1.115) compared with neutral condition (M = 3.940, SD = 1.129) or persuasive condition (M = 3.935, SD = 1.054). However, the ANOVA test between four conditions was not significant (f = 0.584). Therefore, H3 is not supported.

6.4.4 Perceived Control by Experimental Conditions

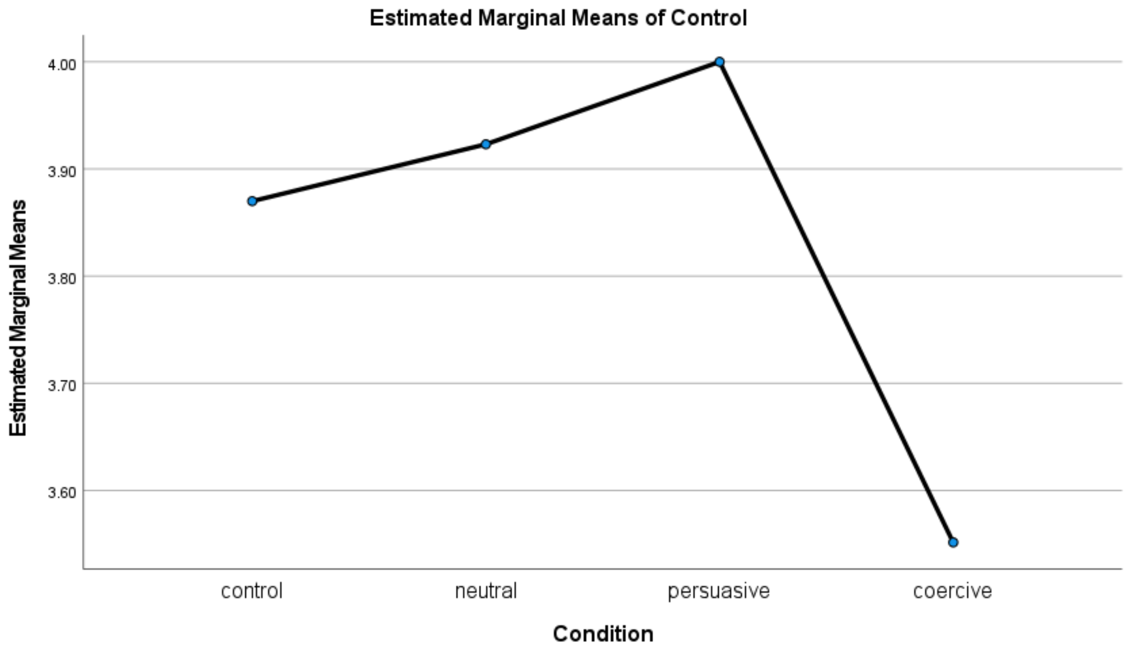


Figure 20 Perceived Control by Experimental Conditions

Regarding the perception of perceived control, the coercive condition incurs the lowest level of perception. The ANOVA test is significant (f = 4.416, p < 0.01). I also conducted a post hoc analysis to explore whether the difference is significant between conditions. The LSD post hoc results show that perceived control in the coercive condition is significantly different from the control condition (p <0.05), the neutral condition (p <0.01), and the persuasive condition (p <0.001). Therefore, H4 is supported.

6.4.5 Perceived Understanding by Experimental Conditions

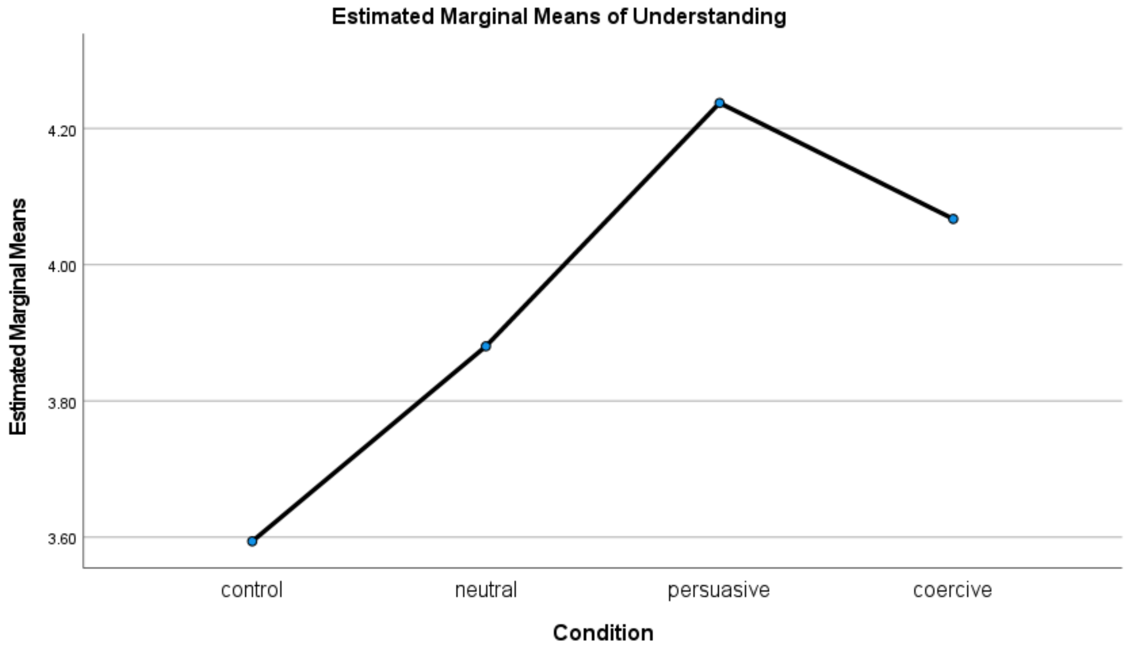


Figure 21 Perceived Understanding by Experimental Conditions

In terms of perceived understanding, participants in the persuasive condition had the highest sense of it. ANOVA test is significant (f = 6.833, $p < 0.001$). Through a post hoc LSD test, the significant difference is between the control condition with the persuasive condition ($p < 0.001$), and the control condition with the coercive condition ($p < 0.01$). The perceived understanding in the neutral condition is not significantly from other conditions. Therefore, H5 is partially supported.

CHAPTER 7: Discussion

The objectives of this study are to (1) identify the antecedents and consequences of different types of trust perceptions (emotional trust and cognitive trust) in intelligent advice-giving systems and how trust perceptions lead to reuse intentions of the systems; (2) to examine how various design features influence users' knowledge levels and further influence their trust perceptions; (3) to explore how different types of trust perceptions (emotional trust and cognitive trust) influence behavioral trust which is the acceptance of advice from intelligent advice-giving systems and factors that moderate the relationship. To answer the questions, I build a research model based on Persuasion Knowledge Model (PKM) and trust theories. I also review the literature on persuasive designs and identify three design features (anthropomorphic features, persuasive features, and interventional styles) and employ them in the experimental conditions. I test the research model using an online experiment and collected 442 valid responses. In general, the findings give empirical support for the proposed research model in the paper.

First, the anthropomorphic features employed in the study successfully created the mind perception of AGS. In conditions that employ animated and emotional expressive avatars, participants believed the system was able to think. The coercive condition didn’t perform well in the closeness perception and co-presence perception. This is probably because the authoritative intervention styles could create a distance between users and the virtual advisor and reduce the feeling of anthropomorphism in the closeness aspect and the co-presence aspect. I further found that the perception of anthropomorphism is a significant antecedent of emotional trust. In other words, the anthropomorphism of a system helps build emotional trust: people are more likely to feel comfortable using a system that is more human-like to them. Moreover, I was able to identify that among the different dimensions of anthropomorphism, co-presence is the dominant sub-construct that contributes to this significant relationship. Perceiving a system as being able to think (anthropomorphism-mind perception) and or perceiving it as a close friend (anthropomorphism-closeness) don't result in emotional trust significantly. This discovery emphasizes the critical role of creating the perception of co-presence in creating anthropomorphism in order to build emotional trust during persuasion or advice-giving.

Second, analysis results also indicate that perceived benevolence is a prominent antecedent of both types of trust. In other words, perceiving the system to put users' interests first and have good intentions for users is positively related to feelings of security as well as assessments of its competence. This is in line with past literature that perceiving the goodwill of the persuader leads to trust (Jones 1996). This finding implies that persuasive AGS should imply goodwill for its users. Examples may be presenting an upfront claim or sending messages about putting users' interests as a priority, thus assuring users and building trust.

Third, the findings suggest that perceived control is another significant predictor of both types of trust. Using an authoritative intervention style evidently reduces perceived control of users and sequentially causes a drop in trust levels. However, the perceived control in the persuasive condition with the facilitative intervention style didn't have a significant difference compared with the neutral or control condition without persuasion. This finding suggests that system designers should be careful with the way of intervening. For instance, the tone of persuasion should be crafted to imply freedom of decision so users won't feel a loss of control. Granting users perceptions of control, even just a little bit can greatly enhance trust (Dietvorst et al. 2018).

Fourth, I found that perceived understanding is a significant antecedent of cognitive trust and the explanation facilities significantly increased perceived understanding in the persuasive condition. This finding indicates the importance of the system to provide explanations while giving advice. When intelligent AGS tries to persuade users to take its advice, it's crucial to provide reasonings or why and how it comes up with the recommended option for the user. Through understanding the reasoning process of the system, users are more likely to view the system as competent and believe its advice as acceptable and rely on the system emotionally. It is thus urgent for system designers to advance AI explainability and strive to convert the "black box" of AI algorithms into a "glass box" (Rai 2020).

Fifth, results show that both emotional trust and cognitive trust are significant antecedents of reuse intention of AGS. I also distinguish between the intention to delegate the future decision to AGS and the intention to use AGS as an assistant. I found that both emotional trust and cognitive can effectively influence intention to delate and intention to let assist. Additionally, I conducted the mediation analysis to test the mediation effect of trust. The results essentially validate the mediating model of trust that knowledge developed during persuasion leads to trust and eventually the reuse intention of the system. To be more specific, two types of trust (emotional trust and cognitive trust) fully mediated the relationship between perceived benevolence and reuse intentions and partially mediated the relationship between perceived control and reuse intentions. Emotional trust partially mediated anthropomorphism perception and reuse intentions while cognitive trust fully mediated perceived understanding and reuse intentions. These findings suggest that in order to have a higher adoption intention of intelligent AGS and build long-term relationships with users, building trust with users is necessary and crucial.

Last but not least, this study was able to measure users' behavioral trust as advice-taken. I find that emotional trust and cognitive trust can predict users’ behavior trust, but the relationships are moderated by users’ characteristics. Trust propensity moderates the relationship between emotional trust and behavioral trust while topic expertise moderates the relationship between cognitive trust and behavior trust. In particular, when emotional trust is developed in people less prone to trust others, it’s more predictive of their trusting behavior which is advice-taking in the AGS context. Similarly, when cognitive trust is developed in people who lack expertise in the domain, it is more likely to lead to behavioral trust. This finding sheds light on how to encourage users to take system advice by targeting users with different characteristics.

CHAPTER 8: Limitations and future research

This study is not without limitations and opens opportunities for future research.

First, participants in the experiment experienced an imaged scenario to finish the task. Although past research has commonly used hypothetical situations to measure users' perceptions and behaviors, it may not reflect their actual behaviors when making real decisions in life. The task in the experiment may also be less complex or rather simplified compared with real purchase decisions. Future research can solve this issue by conducting field experiments in a given situation. It would also be interesting to conduct longitudinal studies to measure users' trust dynamics toward intelligent AGS in different phases of interaction.

Second, there are rich opportunities to advance the persuasive features in the study. To avoid the "uncanny valley" effect, in the experiment, I used a cartoon female character as the avatar of the virtual agent. It would be interesting to explore other representations of a virtual human agent. For example, whether a male agent would make a difference compared with a female agent. Whether enabling the voice of the agent would enhance the trust levels. Other intervention styles can also be proposed and tested to achieve optimal persuasion effectiveness.

Third, future research should investigate more user characteristics and test whether they may moderate the relationships in the model. For example, demographics like gender or age may serve as moderators in the trust formation process or influence how trust perceptions may affect behaviors or reuse intentions.

Lastly, this study is conducted in the U.S and participants need to reside in the U.S and be 18 years or older. Future research may extrapolate the study to different countries with their own cultures and find out whether the trust mechanism toward intelligent AGS may differ.

CHAPTER 9: Conclusion

Intelligent Advice-giving Systems have reached a new level of influence on users' decision-making as AI technology advances. Drawing on the persuasion knowledge model and trust theories, this study identifies the knowledge structure under persuasion as antecedents of trust perceptions on intelligent AGS. It then examines how trust perceptions can lead to trusting behaviors and reuse intentions of the system. Moreover, the study proposes persuasive designs that aim to influence users' knowledge levels and eventually their trust and reuse intentions. The results largely support the research model that trust perceptions serve as mediators between users' knowledge and behaviors and reuse intentions. The study has significant theoretical and practical implications and opens a plethora of research opportunities for investigating intelligent AGS in diverse contexts.

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APPENDIX

TASK INSTRUCTIONS:

While participating in this study, do your best to imagine yourself in the following task scenario: You are being required to purchase **renters insurance** as a condition of renting a new apartment. **An intelligent virtual agent** you interact with will present you with various insurance plans that will **meet the requirements** of your landlord. The virtual agent will ask you several questions and will use your answers to help you find the most suitable plan. Please answer the questions honestly and review the plan options carefully.

SCENARIO:

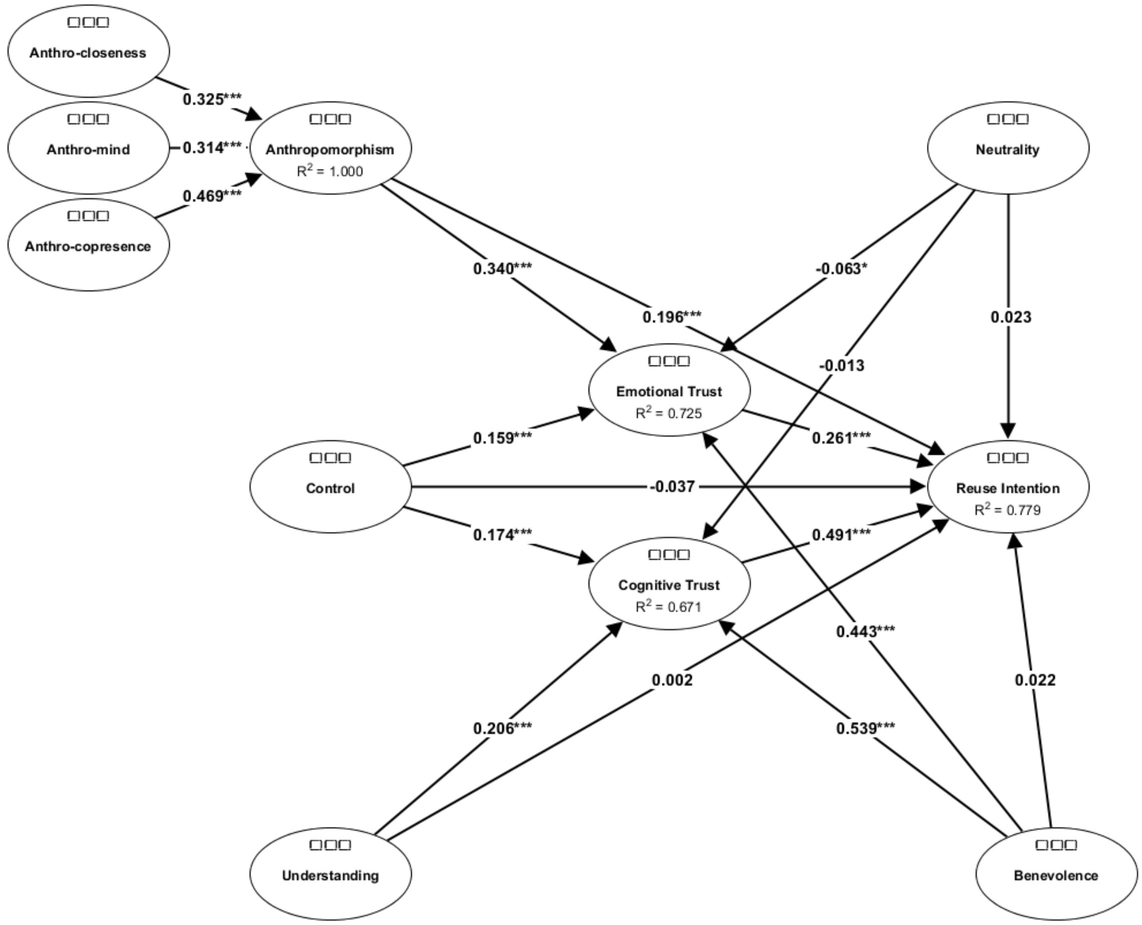
You have recently relocated to a new city and are looking for an apartment. There is one apartment that you like very much and you have decided to apply as a tenant. You are now reviewing the lease agreement and preparing for your application for the landlord.

The landlord of this property is requiring that you buy renter's insurance with a certain amount of coverage. You have decided to use an intelligent virtual agent that offers advice on renter's insurance. The virtual agent will ask for your information and provide insurance options that meet the minimum requirements set forth by your landlord. Moreover, she will present a **"recommended option"** for you **based on her "self-learning" from past data**. Note that the policy options differ in their coverage amount and categories even though the final price may be similar.

You will need the following apartment information to get the proper insurance plans recommended to you:

The place you wish to rent is a two-storey apartment. It has 2 bedrooms, 2 bathrooms and approximately 1,300 sf of living space in total. It is located in the area with zip code "33133". The apartment was built in 2001. You are going to live in the apartment with your partner and all residents are required to be included in the renters insurance.

Mediation Results in Adanco



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