UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

A quantitative study exploring possible determinants for consumer trust in AI

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A Master's degree project in Marketing & Consumption, Graduate School

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ABSTRACT

In this study, we examine factors which determine consumer trust in AI and explore challenges and opportunities in relation to these. Through investigating previous findings regarding online trust and trust in AI, we hypothesized that data transparency and anthropomorphism would have a direct effect on trust in AI, and that privacy concern and personal relevance would moderate these relationships. A 2x2- between-subject experiment was conducted, where anthropomorphism and data transparency were manipulated in fictitious shopping scenarios. The results concluded that anthropomorphism was not a predictor, while data transparency had a significant direct negative impact on trust in AI. Privacy concern and personal relevance were not shown to moderate any of the proposed relationships. Instead, privacy concern had a direct, negative impact, and personal relevance had a direct positive relationship with trust in AI. Altogether, we conclude data transparency and privacy concern negatively affects trust, whereas personal relevance is a strong positive predictor of trust in AI. Making content personally relevant through the use of AI, was identified as one of the main opportunities for marketers, while privacy concern and data transparency may pose a challenge for companies.

Keywords: *Artificial Intelligence (AI), Consumer trust, Anthropomorphism, Data transparency, Privacy concern, Personal relevance*

INTRODUCTION

The modern-day consumer expects personalized, seamless and fast online experiences (PWC, 2020). Today, we use what is known as web 3.0 (Almeida, 2017; Nath & Iswary, 2015), where personalization of messages, content and offerings are key (Earley, 2017; Guzman & Lewis, 2020; PWC, 2020). To meet consumer demands, access to customer data (Pigni, Piccoli & Watson, 2016) and decision-making by computers are integral (Syam & Sharma, 2018; Popescu, 2018). Artificial intelligence (AI), is an essential tool in this changing marketing landscape (Earley, 2017; Popescu, 2018; PWC, 2020; Adadi & Berrada, 2018). In essence, AI is an automated system which uses machine learning, an application which allows the AI to process vast amounts of data, and through iterations learn and improve its output (Syam & Sharma, 2018; Earley, 2017). For instance, Harley Davidson used AI to increase the number of identified potential customers by almost 3000% (Power, 2017).

If the development of the web proceeds as predicted, humans and machines will interact in symbiosis in the web 4.0 (Almeida, 2017; Nath & Iswary, 2015). A core strength of AI lies in its inherent ability to mimic human behavior, which specifically emphasizes cognitive function (Syam & Sharma, 2018). AI is being increasingly integrated into individuals' daily lives (Adadi & Berrada, 2018), through product and service recommendations, and through the use of digital assistants such as Apple's Siri (Guzman & Lewis, 2020; Nath & Iswary, 2015; Adiadi & Berrada, 2018). Yet, consumers are not necessarily aware that they are interacting with AI (PEGA, 2019). The transition towards using AI has begun at the grander scale (Iansiti & Lakshani, 2020; Popescu, 2018), as many companies have recognized the potential to improve their business (Wilson & Daugherty, 2018; Popescu, 2018). Companies are seemingly enthusiastic to increase the use of AI in their businesses, but do consumers share this excitement and how does it affect trust between the parties?

In the EU, trust in the internet was at its lowest in a decade in 2018 (European commission, n.d.). This finding came in spite of the introduction of the general data protection regulation (GDPR) which aims to regulate use of personal data to protect user privacy (Ooijen & Vrabec, 2019; European commission, 2018) The framework also aims to improve consumer trust in an online setting (European commission, 2018). However, the framework has received criticism for hindering innovation, being too difficult to understand (Chivot & Castro, 2019) and to fail to properly protect users (Ooijen & Vrabec, 2019). Consumer trust in AI technologies has been identified as one of the greatest challenges to continuously improve the online customer journey (PWC, 2020). Business studies have indicated that consumers lack trust in AI (PEGA, 2019; Enkel, 2017; Larsen & Hunt, 2018), due to for instance insufficient communication (Enkel, 2017), and perceived risks regarding safety and control of personal data (Schierberl, 2019; PWC, 2020). As the use of AI in marketing is growing, trust is imperative for consumers to try both new services and products (European commission, 2018), and to adopt AI as a concept (Rossi, 2019; Sethumadhavan, 2019).

Building trust with consumers is highly important for retailers as it is needed to build long-term relationships with consumers (Wu et al., 2012; Liu et al., 2004), and has been shown to positively affect loyalty, satisfaction and in turn, profitability (Schoenbachler & Gordon, 2002). If trust is lacking in the online environment, consumers are unlikely to provide personal information (Morey, Forbath & Schoop, 2015; Liu et al., 2004; Taddei & Contena, 2013; Zimmer et al., 2010; Joinson et al., 2010), which is the fundamental enabler of success for companies which employ AI. While there is evidence supporting that people may be willing to disclose more information to an AI rather than to a human in the online sphere (Sethumadhavan, 2019), a global survey concluded that a vast majority of consumers preferred chatting with a human online rather than an AI agent (PEGA, 2019).

Within the online trust field, a multitude of trust-building determinants such as website design features (e.g Bart et al., 2005; Kim & Moon, 1998), and privacy statements (Lauer & Deng, 2007) have been investigated. Antecedents for trust in AI, has to some extent been studied, mainly within the automotive (e.g Collingwood, 2018) and medicine field (Hengstler, Enkel & Duelli, 2016; Nundy, Montgomery & Wachter, 2019). Aspects such as user control (Collingwood, 2018) and system transparency (Nundy, Montgomery & Wachter, 2019) were identified as important factors in these contexts. For consumer activities, trust in AI has mainly been limited to trust in recommender systems (Benbasat, 2006; Pu & Chen, 2007). There is still a lack of research studying trust in AI for modern, consumer-facing applications of the technology, where it is integrated into several stages of the customer experience.

The purpose of this study is to investigate factors which determine trust in AI in order to contribute to the online trust field in relation to disruptive technologies. It is also a response to Bauman & Bachmann (2017) calls for further academic research in the trust field regarding web 3.0. The aim of the study is thus to measure and analyze determinants which may affect consumer trust in AI, and the study seeks to answer the following research questions:

- *What factors determine consumer trust in AI?*
- *What are opportunities and challenges relating to consumer trust in AI?*

The context of the study is the online apparel industry from a consumer perspective.

DELIMITATIONS

In Europe, GDPR regulates how personal information online may be used by companies (Ooijen & Vrabec, 2019), affecting for instance, how and when consent is given to one’s personal information. It is important to note that such aspects reflected in this study represents legislation in the EU.

This study takes place in Sweden, where the number of people who can be considered high-frequency online shoppers has increased significantly since 2016 (E-barometern, 2019a), and clothing- and shoes is the most popular segment to shop online (E-barometern, 2019b). Trust in AI differs across industries (Schierberl, 2019; PEGA, 2019), making it difficult to generalize studies concerning trust in AI. This research is limited to the apparel industry and compared to other industries, users are most likely to trust AI-generated advice in retail (Schierberl 2019; PEGA, 2019).

The layout of the paper is as follows; first, important concepts will be clarified and previous research on online trust and trust in AI is presented to provide an overview of the research fields. Second, hypotheses will be presented based on a theoretical framework, followed by a methodological discussion and study procedure. Then, results will be presented and analyzed, followed by theoretical- and managerial implications and recommendations for future research. Lastly, a brief conclusion and contribution of the study is offered.

LITERATURE REVIEW

Trust and reliance

Common for all situations requiring trust formation, is that there are two parties, and the presence of vulnerability is in the trusting party (Bauman & Bachmann, 2017). This reflects the aspect of risk involved when there is a need for trust (Sutrop, 2019). Many scholars agree that overall trust consists of three dimensions; competence, integrity and benevolence (Chen & Dhillon 2003; McKnight & Chervany, 2001). For automated systems, trust entails relying on the system when such risks are present (Hoff & Bashir, 2015). Previous research has discussed whether or not one can be said to have trust in AI (Sutrop, 2019; Coeckelbergh, 2012; Taddeo, 2010), assuming trust can only be formed between peers, for which AI does not qualify (Sutrop, 2019). A term offered instead of trust, is to *rely* on an automated system (Sutrop, 2019; Coeckelbergh, 2012; Hoff & Bashir, 2015). As reliance mainly refers to system functionality and predictability (Sutrop, 2019; Coeckelbergh, 2012), and AI is invisible to the user (Pandya, 2019), apparel consumers will likely not evaluate the function of the system which would call for using reliance in this study. In addition, trust in AI often extends to the actor providing the application (Hengstler, Enkel & Duelli, 2016; Winfield & Jirotka, 2018; Sutrop, 2019). As such, other information such as communication, interface or behavior of the actor will form the basis for trust evaluation, which is why trust will be used in the remainder of this research.

This study adopts the approach taken by several scholars, considering AI and the company which employs it as agents in which trust can be placed (Coeckelbergh, 2012; Taddeo, 2010; De Visser et al., 2012; Corritore, Kracher & Wiedenbeck, 2003). In addition, it defines trust as existing when a trusting party has confidence in an agent's integrity (Morgan & Hunt, 1994) and can rely on them (Morgan & Hunt, 1994; Pieters, 2011). Reliability and integrity are associated with honesty, consistency, benevolence and competence (Morgan & Hunt, 1994). In this definition of trust, both a cognitive and affective dimension are included, required for general trust formation (Soh, Reid & King, 2009). Affective trust is concerned with emotional responses and based on feelings, while cognitive trust is a process of rational thinking and cognitive effort to evaluate available information (Soh, Reid & King, 2009; Punyatoya, 2019).

A review of antecedents to online trust

Online trust is not fundamentally different from traditional face-to-face trust formation (Bauman & Bachmann, 2017), where both involve risk and vulnerability (Corritore, Kracher & Wiedenbeck, 2003; Beldad, de Jong & Steehouder, 2010). A noteworthy difference however, is that online, a human has to trust an object created by a human rather than another human directly (Corritore, Kracher & Wiedenbeck, 2003). This eliminates the possibility to form instinctive trust as one could when encountering another person (Hoff & Bashir, 2015). Another central difference is that assessing trustworthiness online is more difficult than offline as it entails a multitude of actors and aspects (Friedman, Kahn & Howe, 2000). Trust is a key factor online (McRobb, 2006) as the development of trust online between businesses and consumers can invoke positive attitudes, and reduce perceived risk which in turn improves willingness to provide information (Liu et al., 2004). Studies also show trust has a direct effect on behavioral intentions (McKnight & Chervany, 2001; Liu et al., 2004; Bart et al., 2005). There are many antecedents which have been found to affect online trust. For a summary of its' antecedents, see table 1.

ANTECEDENTS	STUDIES	FINDINGS
Website design factors		
Ease of navigation & presentation on website	Bart et al., 2005; Beldad, de Jong & Steehouder, 2010; Nielsen et al., 2000	Had a significant effect on trust online: strongest for sites which are information intensive
Visual design elements of website	Kim & Moon, 1998; Bart et al., 2005; Beldad, de Jong & Steehouder, 2010	Were found to have a significant effect on trustworthiness online
Website content & content quality	Liao, Palvia & Lin, 2006; McRobb, 2006	Found to increase consumer beliefs of usefulness & trust online
Transactional factors		
Perceived security of online transaction	Yoon, 2002; Bart et al., 2005	Were found to have a significant effect of web-site satisfaction & trust online
Perceived technological trustworhtiness	Corbitt, Thansankit & Yi, 2003	Essential factor of trust in an online vendor
Order fulfillment	Bart et al., 2005	Influential determinant of trust online, mainly for websites where information & involvement risks are high
Brand & consumer factors		
Brand reputation	Chang, Cheung & Tang, 2013; McKnight & Chervany, 2001; Chen & Dhillon, 2003; Metzger, 2006	Positive effect on consumer trust online
Brand strength	Bart et al., 2005	Significant determinant of online trust. Most important for automobiles, financial services, computers and community sites. Higher influence of people with higher education than those with lower education.
Consumer rating systems	Bauman & Bachmann, 2017	Found to be an online trust signal
Offline presence of online vendor	Chen & Dhillon, 2003	Can affect trust online
Offline marketing activities	Corbitt, Thansankit & Yi, 2003	Had a positive effect on consumer trust online
Return policies	Chang, Cheung & Tang, 2013	Showed a positive effect on consumer trust in an online vendor of which has established a good brand reputation
Privacy factors		
Privacy concern	Ermakova et al., 2014; Aïmeur, Lawani & Dalkir, 2016; Wu et.al, 2012; Bart et al., 2005	Had a negative effect on trust online
Privacy statements	Pan & Zinkhan, 2006; Lauer & Deng, 2007	The existence of privacy statements, showed a positive effect on trust online
Third party certifications	Chang, Cheung & Tang, 2013; McKnight & Chervany, 2001; Chen & Dhillon, 2003; Kimery & McCord, 2002; Bahmanziari, Odom & Urgin, 2009	Have shown to both have a positive and negative effect on trust online

TABLE 1: Antecedents for online trust

Previous findings on trust in AI

Most researchers studying AI agree that trust is essential for its' success and adoption as it is a complex process to understand (Kuipers, 2018; Winfield & Jirotka, 2018; Hengstler, Enkel & Duelli, 2016; Sutrop, 2019; Pieters, 2011; Coeckelbergh, 2012; Lee et al., 2015). Previous studies have investigated trust in AI mainly in the automotive industry, and found that it is negatively affected by privacy and liability concerns (Collingwood, 2018), and positively affected by system transparency, technical competence and user control (Choi & Ji, 2015; Hengstler, Enkel & Duelli, 2016). In addition, anthropomorphism, ascribing human traits to a non-human object, has been found to increase trust in the system (Waytz, Heafner & Epley, 2014; Ruijten, Terken & Chandramouli, 2018; Lee et al., 2015). Similarly, designing for automated systems to follow social norms has been shown to increase trustworthiness (Kuipers, 2018). Celmer, Branaghan & Chiou (2018) suggested that the relationship between humans and automated systems exist in the context of a brand, where brand personality and system performance are both integral for trust. Studies in the field of medicine have emphasized the need for balance between automation and human factors to enable trust, and transparency and competence of the system (Nandy, Montgomery & Wachter, 2019; Hengstler, Enkel & Duelli, 2016). It is also important to enable the user to understand the technology (Hengstler, Enkel & Duelli, 2016). Lee & See (2004) proposed trust in automation has three bases, purpose, performance and process. Purpose refers to the intention the system designer had when constructing the system, and is beyond the scope of this study since the focus is on the consumer setting. Performance and process will be discussed in the development of hypotheses.

As AI is getting smarter and becoming increasingly incorporated by businesses for a wide variety of business enhancing solutions (Sethumadhavan, 2019; Rossi, 2019; Nath & Iswary, 2015; Adadi & Berrada, 2018), there are considerable risks and challenges to take into account. For instance, market disruption due to changing market structures when adopting AI (Iansiti & Lakhani, 2020), may affect the basis of competition and profitability for an entire industry. On a consumer level, it is important that the technology is perceived as fair, unbiased, transparent (Rossi, 2019; Nundy, Montgomery & Wachter, 2019).

THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

Anthropomorphism

Many trust-studies both on- and offline are based on human-to-human interaction, with which trust in automation shares many similarities (Hoff & Bashir, 2015). There are however, important differences in the concept of trusting an automated system or a human being. Instinctive trust is often used to evaluate the message of a human agent, something which cannot transfer to systems (Hoff & Bashir, 2015). Instead, machines are expected to perform perfectly, and if it fails to do so, trust decreases more than it would for human agents and may be more difficult to rebuild (De Visser et al., 2012; Hoff & Bashir, 2015). Anthropomorphism means ascribing human-like characteristics or behavior to non-human entities and is a process which happens without giving it much thought (Kim & Sundar, 2012a). Such instinctive acting entails treating the machine the same way one would a human and respond accordingly (Nass et al., 1995; Verhagen et al., 2014). This process has been shown to increase trust in AI (Hoff & Bashir, 2015; Waytz, Heafner & Epley, 2014; Lee et al., 2015; Ruijten, Terken & Chandramouli, 2018), often by provoking a sense of social presence (Lee et al., 2015; Verhagen et al., 2014). Human traits of a system may also increase user satisfaction (Verhagen et al., 2014), which is closely related to trust (Leninkumar, 2017).

Attributes which affect the ascription of human-like characteristics to an automated system include gender (Lee, 2004; Lee, 2007; Waytz, Heafner & Epley, 2014), and style of language (Schulman & Bickmore, 2009; Nass et al., 1995; Guzman & Lewis 2020), such as a conversational interface (Ruijten, Terken & Chandramouli, 2018; Guzman & Lewis 2020). Personality (Nass & Lee, 2001; Lee et al., 2015), socially favorable behavior (Hoff & Bashir, 2015; Verhagen et al., 2014), and name (Nass et al., 1995; Waytz, Heafner & Epley, 2014) are also attributes which affect the anthropomorphism process. Kim & Sundar (2012a) note that these attributes are easily manipulated and may be called “anthropomorphic cues” as they remind the user of human-like traits of the system. As anthropomorphism has been shown to increase trust in AI (e.g. Waytz, Heafner & Epley, 2014), and people seem to prefer a human touch over a faceless machine (PEGA, 2019). we pose the following hypothesis:

H1: *Anthropomorphism has a direct positive effect on trust in AI*

Data transparency

There is still a general lack of understanding regarding how personal data is used online (Cottrill & Thakuriah, 2015; PEGA, 2019; European Commission, 2019; Morey, Forbath & Schoop, 2015). While many online users may be aware sites are collecting data about them, they often lack knowledge on what specific data is collected (Morey, Forbath & Schoop, 2015; PEGA, 2019; Joinson et al., 2010). There is not yet extensive research focusing on consumer perceptions of the information collection process needed for personalized offerings (Aguirre et al., 2015). However, studies which have suggested that transparency lead to positive behavioral intentions (Aguirre et al., 2015) and increased trust (Krasnova, Kolesnikova & Günther, 2010), have mainly been tested by making the user aware of the data collection. This has not necessarily involved details regarding what type of information is concerned.

In general, users only become aware of the large amount of data collected when companies explicitly inform them (Aguirre et al., 2015). Being able to explain and justify a decision is crucial for AI (Kuipers, 2018; Pieters, 2011; Rossi, 2019; Sutrop, 2019; Pu & Chen, 2007; Adadi & Berrada, 2018), and also one of its biggest challenges (Rossi, 2019). Explanation also constitutes the process dimension as proposed by Lee & See (2004), referring to the user's ability to understand the system which contributes to overall trust.

One of the core objectives of providing explanations is often to increase transparency (Pu, Chen & Hu, 2012). However, transparency of systems explains *how* a system works or a choice has been made, and is not concerned with justifications or explaining *why* (Pu, Chen & Hu, 2012; Pieters, 2011). When discussing explanations for AI applications, increasing transparency in the system according to this definition does not necessarily increase trust (Pieters, 2011), as such descriptions are often difficult to grasp (Friedman, Kahn & Howe, 2000). For many user interfaces, such as consumer-facing marketing activities, the user is not concerned with understanding the *how* behind the AI algorithm, which is more important for evidence-based industries (Wilson & Daugherty, 2018). Instead, when there is not a significant amount of risk involved, consumers are more likely to be interested in transparency by illustrating the connection between cause and effect, the *why* (Sinha & Swearingen, 2002). Creating confidence in the user by explaining and justifying *why* a decision is made by an automated system is seemingly more related to consumer trust for the apparel industry (Pieters, 2011; Pu, Chen & Hu, 2012; Sinha & Swearingen, 2002; Adadi & Berrada, 2018).

This study defines transparency in relation to an artificial agent as communicating clearly regarding what data is collected and how it is used as well as to explain why a certain decision is made. This will be referred to as *data transparency*. While expert strategists suggest that such transparency has a positive effect on trust (Morey, Forbath & Schoop, 2015), there is a lack of academic support for this in relation to AI-technologies in marketing. In addition, personalization has been shown to have a negative effect on trust due to the aspect of data collection (Bauman & Bachman, 2017). When companies explicitly use personally identifiable information, consumers have also been shown to respond negatively (Wattal et al., 2012). We therefore hypothesize:

H2: *Data transparency has a direct negative effect on trust in AI*

Anthropomorphic behavior of a non-human object seems to increase trust (Hoff & Bashir, 2015; Waytz, Heafner & Epley, 2014; Lee et al., 2015; Ruijten, Terken & Chandramouli, 2018), but findings also indicate that when a robot communicates with a high level of transparency they are perceived as more humanlike which subsequently affects trust evaluations (Brand et al., 2018). Thus, the effect of anthropomorphic cues may be reinforced with high levels of transparency, as the anthropomorphic process may be the dominant feature.

H3: *Anthropomorphism in combination with data transparency will have a stronger positive effect than only anthropomorphism (H1)*

Privacy concern

Disclosing personal information online, is usually a prerequisite to visit a site, complete a purchase and receive personalized service (Joinson et al., 2010). Marketing today is fully dependent on data transactions from users (Pigni, Piccoli & Watson, 2016). Such information is most often collected by a third-party through web tracking using cookies, small text files which facilitate data collection (Techterm, n.d).

Clear information on data collection and use is necessary according to GDPR (Ooijen & Vrabec, 2019), often communicated through privacy policies (Ooijen & Vrabec, 2019; Ermakova et al., 2014). Yet, privacy concerns are one of the biggest consumer issues facing the internet (Bauman & Bachmann, 2017; Pan & Zinkhan, 2006; Wu et al., 2012; Friedman, Kahn & Howe, 2000). Privacy concern mainly stems from a lack of control over one's data (Bauman & Bachman, 2017; Krasnova, Kolesnikova & Günther, 2010) which is central to ensure online privacy (Milne & Gordon, 1993; Bauman & Bachman, 2017; Oijen & Vrabee, 2019). Privacy concern can deter users from visiting a website (Wu et al., 2012; Pan & Zinkhan, 2006; Hoffman, Novak & Peralta, 1999) and has been shown to have a negative effect on online trust (Ermakova et al 2014; Aïmeur, Lawani & Dalkir, 2016; Wu et al., 2012).

When organizations collect vast amounts of customer data, control can be fully lost or unwillingly reduced during the marketing transaction, leading to an invasion in privacy (Milne & Gordon, 1993; Caudill & Murphy, 2000). A majority of EU residents do not feel they have control of personal information provided, a statement which ranks the highest among those who frequently shop online. While GDPR aims to provide users with control, 67% percent of EU residents have heard of the policy, of which 36% knows what it is (European Commission, 2019).

Privacy concerns are often a result of personal dispositions (Karwatzki et al., 2017). Experiencing privacy concern also make people less likely to leave personal information in an online transaction (Dinev & Hart, 2006), take part in personalization services (Awad & Krishnan, 2006) and has been found to moderate trust online (Taddei & Contena, 2013). As transparent communication regarding data collection, highlights the level of personal information provided in an online setting, it is hypothesized that:

H4: *The effect of data transparency on trust in AI is moderated by the level of privacy concern*

Lee (2019) found that when privacy threats are perceived to be high, privacy concerns regarding provision of personal information increased for a non-anthropomorphic agent compared to an anthropomorphic agent. We extrapolate these results and include the notions that anthropomorphism seems to increase trust (e.g. Lee et al., 2015; Ruijten, Terken & Chandramouli, 2018) while privacy concern decreases trust (e.g. Aïmeur, Lawani & Dalkir, 2016, Wu et al., 2012). Based on this, it can be argued that for people who experience privacy concerns, encountering a human-like agent will impact the relationship between anthropomorphism and trust in AI more than for those who do not tend to experience privacy concern. It is hypothesized that:

H5: *The effect anthropomorphism on trust in AI, is moderated by the level of privacy concern*

Personal relevance

For trust to be established between a company and consumer, some degree of familiarity is required. This can be created through marketing messages showing consumers potential benefits which the company can offer (Wu et al., 2012). Perceptions of benefits are highly subjective, and personalizing messages is a fundamental part of the concept of personalization, which denotes the extent which consumers feel content offered is relevant to them (Lee & Park, 2009).

Personalization has been discussed diligently in the marketing literature (e.g. Kramer & Thakkar, 2007; Zhang, 2011; Tucker, 2014; Oberoi, Patel & Haon, 2017; Krajicek, 2015). In relation to trust, it has been argued to be a condition for its formation (Briggs, Simpson and De Angeli 2004). Personalization has also been shown to increase both cognitive and emotional trust for recommender systems (Benbasat, 2006). Such individual adaptation has mainly become a desirable feature due to its ability of producing content that is of personal relevance to users (Kim & Sundar, 2012b). Addressing customers by their name and creating product service matches are examples of tools which through AI are used to make content personal and relevant (Verhagen et al., 2014).

Personal relevance online has been shown to have a positive effect on information disclosure (Zimmer et al., 2010), behavioral intentions (Morris, Choi & Ju, 2016), and user perceptions online (Kim & Sundar, 2012b). Personal relevance may be likened to what Lee & See (2004) call performance, a basis of trust in automation, and refers to the ability of the algorithm to achieve a specific users goal (Lee & See, 2004). Perceptions of the quality of product recommendations have been shown to affect user evaluations of the recommender system (Knijnenburg et al., 2012). If an online shopping experience is personalized to an individual successfully, the person should experience high personal relevance of communication and product/ service recommendations.

Contrary to popular findings, personalization has also been shown to have a negative effect on trust due to the aspect of data collection (Awad & Krishnan, 2006; Bauman & Bachmann, 2017), which may provoke privacy concerns (Kim & Huh, 2017). This need for balancing of objectives is often referred to as the personalization privacy paradox (Awad & Krishnan, 2006, Karwatzki et al., 2017) However, findings also indicate that when consumers take part in transactions online, they find the personalization aspects beneficial as long as they are relevant to the individual, regardless of possible privacy concerns (Kim & Huh, 2017; McDonald & Cranor 2010; Ur et al. 2012; Pu, Chen & Hu, 2012). Similarly, the amount of personal information that users are willing to disclose, is often a tradeoff between perceived usefulness of recommendations and privacy concerns (Knijnenburg et al., 2012). This may entail that consumers care less about potential concerns regarding the information collected, demonstrated through high data transparency in an online interaction.

H6: *The effect of data transparency on trust in AI, is moderated by personal relevance*

As findings indicate that perceived relevance could make users disregard possible privacy concerns (e.g. McDonald & Cranor, 2010), possibly even override them (Karwatzki et al., 2017) the following hypothesis is formed:

H7: *The moderating effect of privacy concern between data transparency and trust in AI will disappear when introducing personal relevance as an additional moderator*

Figure 1 aims to summarize and illustrate variables which have been hypothesized to have an either direct or moderating effect on trust in AI.

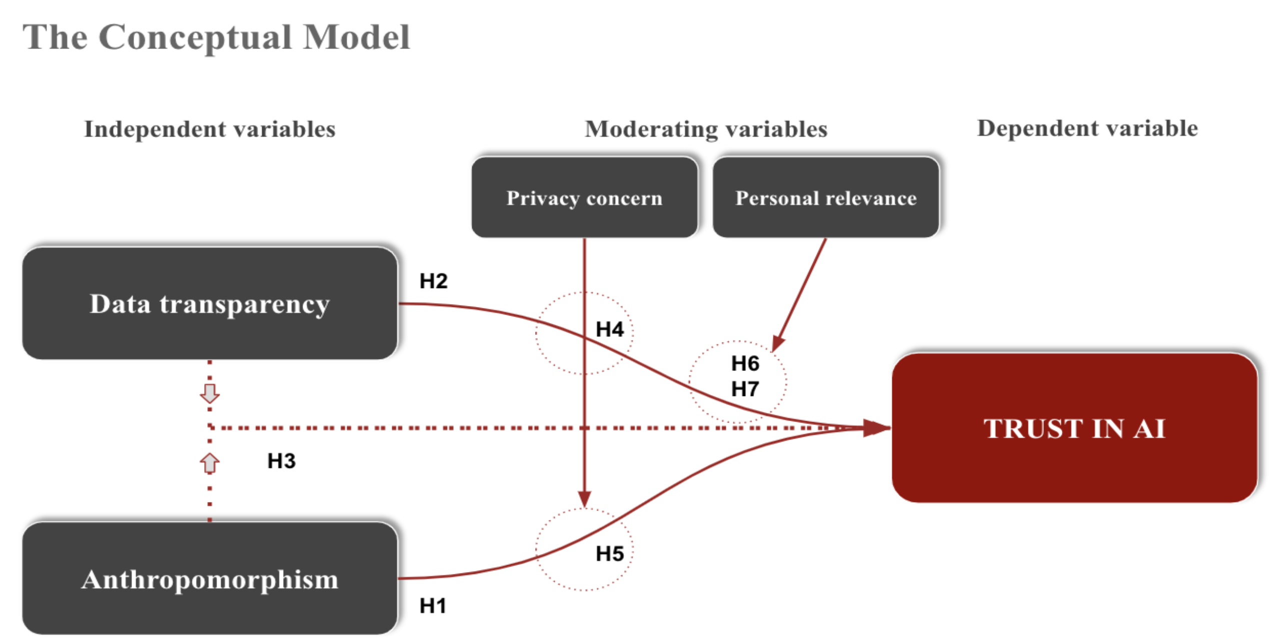

FIGURE 1: Conceptual Research Model

METHODOLOGY

Design and Objective

As the intention was to test the effect of two independent variables to elaborate on the phenomena of trust, and to isolate cause and effect, an experimental approach was chosen (Geuens & De Pelsmacker, 2017). A 2x2 between-subject factorial design (see figure 2) was applied to accommodate testing of the two cause variables (Söderlund, 2018), manipulated in four different scenarios. A text-based scenario survey with figurative elements was constructed where respondents were asked to immerse themselves in a fictitious online apparel shopping experience, where every event, piece of information and action was predetermined by the researchers.

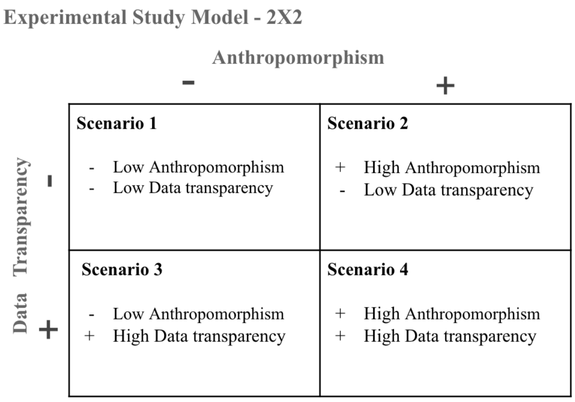

FIGURE 2: Experimental study design

Development and pre-test of survey

Phase one of the scenario construction concerned what events and information to be included, and was carried out using relevant research, observed practices from leading apparel companies, and expert opinions (Carbonell, Sánchez-Esguevillas & Carro, 2017). Using expert judgements to design a scenario may be considered sufficient for situations concerning personal decisions (Culka, 2018; Presser & Blair 1994). However, the choice was made to supplement the data using additional information sources to provide a more realistic end-result (Fulton Suri & Marsh, 2000) and maintain high quality of the stimuli (Geuens & De Pelsmacker, 2017). As task realism is a common threat to the external validity of experiments (McDermott, 2011), the researchers tried to reflect reality while maintaining the *experimental realism* as not to interfere with the internal validity of the experiment (McDermott, 2011). An obvious limitation of online surveys is that there are influencing factors outside of the researcher's control, such as the respondent's mood and surrounding environment (Iarossi, 2006). While these issues are inherently hard to handle, the respondents were encouraged to immerse themselves in the experience with the help of visual aids. Images were created and included to reflect a realistic website design and the AI elements reflected common uses of AI, namely a chat-bot and product recommendations.

Expert opinions from one of the world's leading personalization platforms for Ecommerce, Nosto, was solicited (Nosto, n.d.). As the objective of the present research was to investigate individual experiences, the scenarios constructed followed a narrative, persona-centered design, as suggested by Madsen & Nielsen (2010). To avoid subjective influences such as brand preference, such aspects were fictitious by design (Melero & Montaner, 2016; Lii & Lee, 2012; Geuens & De Pelsmacker, 2017). When designing the manipulations for anthropomorphic cues, aspects were chosen based on theory (see section "anthropomorphism" in theoretical framework). Designing the manipulations of data transparency, aspects were included based on discussions with Nosto and available information regarding consumer awareness of such aspects (see "data transparency" in theoretical framework). Experiments which are fictitious by design, may be considered to have limited generalizability due to not being perceived as realistic (Chang, Cheung & Tang, 2013) and thus have less explanatory power than field experiments. However, participant reactions do not seem to differ significantly from their real-life counterparts (Söderlund, 2018). In addition, controlled environments such as those created for this study have been shown to reduce biases caused by memory and rationalization tendencies (Grewal, Hardesty & Iyer, 2004). It is also particularly useful to study how humans make multi-dimensional judgements and choices (Hulland, Baumgartner & Smith, 2018).

Prior to the main data collection, a pre-test was performed which included a small-scale quantitative study, followed by qualitative interviews (Hulland, Baumgarten & Smith, 2018). Feedback was also obtained from Nosto, beneficial for identifying problems of trials (Presser & Blair, 1994). The four scenarios were distributed between the 32 respondents. where each individual received one scenario. Next, an individual from each scenario was chosen to guide the researcher through their reasoning when answering the questions (Presser & Blair, 1994). The goal was to gain useful insights and feedback on how to eliminate the risk of misunderstandings, and to confirm the intended outcome of the manipulations (for an example of differences between scenario manipulations, see appendix Ⅰ).

Measurements

Multi-item scales were used to measure the variables, to prevent measurement issues that can occur by using single item scales (Hulland, Baumgartner & Smith, 2018). All scales had been previously validated in academic studies, to ensure construct validity (Geuens & De Pelsmacker, 2017). Perceptions of *multidimensional trust* was measured using a trust scale developed by Soh, Reid & King (2009), which has been used to measure trust in AI in the context of autonomous vehicles (Lee et al., 2015). The original scale included several items to measure the cognitive dimension of trust (Soh, Reid & King, 2009), of which four have been included in the current study. Items which could be considered as variations of the same concept were all combined to be included in one word, and these revised constructs were validated by Lee et al. (2015). Seven items were thus included to measure overall trust, where four represented the cognitive dimensions, and three represented the affective dimension (Soh, Reid & King, 2009).

Privacy concern was measured using the multidimensional instrument created by Smith Milberg & Burke (1996), developed by Bellman et al. (2004) to fit the online environment. The adapted scale reflects overall information privacy concern online, and includes several dimensions such as “data collection”, “improper access”, and “unauthorized secondary use” (Bellman et al., 2004). Since the study aimed at capturing inherent individual privacy concerns in regard to the data collection process, this was the only dimension which was included in the study. Finally, to measure the construct of *personal relevance*, items were adapted from the scale developed by Mishra, Umesh & Stem (1993) which has been tested in an online setting (Zimmer et al., 2010). One of the five original items, “relevant” was disregarded as it is highly subjective and was difficult to incorporate into a standardized scenario where all choices had already been made. The idea was to understand whether or not the type of help and advice offered in the scenario were perceived as relevant in an online shopping scenario. For a list of items, see appendix Ⅱ.

Scales were summated to have only one construct representing each variable. Scale reliability was estimated using Cronbach alpha to ensure internal consistency (Connelly, 2011). The scale reliability test yielded the following values for privacy concern, personal relevance and trust: 0.872, 0.901, and 0.917, all above the recommended value of 0.7 (Connelly, 2011). In addition, a few control variables such as gender, age and familiarity with technology have been included in the survey. How familiar a user is with a certain technology or online encounter has been shown to influence the development of online trust (e.g. Beldad, de Jong & Steehouder, 2010) and research indicates that having confidence in both machines and one's own technical capabilities results in a higher propensity to trust AI (Gambino, Sundar & Kim, 2019). Therefore, to control for differences regarding technological interest and perceived ability, a control variable "tech-savvy" was included where respondents were asked to answer yes or no to the question "In general, are you interested in technology and new tech-related products?"

Procedure

The surveys were sent out online to a total of 1284 students at Gothenburg University. Students have been criticized for not reflecting a fair view of the reality (Henrich, Heine & Norenzayan, 2010), and being subject to carelessness bias as a result of answering a multitude of academic surveys (Ashraf & Merunka 2017). However, students have also been proven to provide similar answers as the larger population (Söderlund, 2018; McDermott, 2011; Ashraf & Merunka 2017), specifically when they do not differ significantly on key aspects affecting the research at hand (McDermott, 2011). Relevant to the context of the study, students are argued to be highly involved in consumer activities (Kwok & Uncles, 2005), and are frequent online shoppers who value privacy and trust as important factors in online shopping (Farah et al., 2018). This is similar to general findings on both privacy concern (e.g. Bauman & Bachmann, 2017; Hoffman, Novak & Peralta, 1999; Pan & Zinkhan, 2006) and trust (e.g. McKnight & Chervany, 2001; Liu et al., 2004; Bart et al., 2005). As students are likely to have encountered AI as avid internet users (European Commission, 2019), the sample was considered relevant for the context of the study and thus deemed appropriate (Geuens & De Pelsmacker, 2017). Student emails were collected from the University institution Ladok, anonymized and randomly divided into 4 different test groups, (Söderlund, 2018). Respondents were asked to read the text-based scenario carefully and answer questions regarding their experience. The survey system also allowed for reminders to be sent out to respondents who had yet to answer the survey, whilst protecting their anonymity. Thus, two reminders over the four weeks of data collection were sent out to maximize response rate (Deutskens et al., 2004;). The response rate was 13.6%, which was deemed sufficient (Krosnick, 1999) and similar to other small-scale online surveys (Sauermann & Roach, 2013, Lindstedt & Nilsson, 2014).

Models

To test H1 and H2, simple linear regressions were performed in SPSS, in order to conclude whether or not one or both of the independent variables may be used when attempting to explain any variation in the dependent variable (Hayes, 2017). In order to test the independent variables in a regression model, the two scenarios which included high levels of anthropomorphism (scenarios 2 & 4) were combined into one variable. The same procedure was performed for the two scenarios with high transparency (3 & 4). These new variables were subsequently used in the regression model as the independent variables to be tested against the dependent variable of trust in AI. The new variables were also used when testing the hypothesized moderating variables. A potential issue with linear regression is that it is prone to multicollinearity (Hair et al., 2014). To minimize the risk of such influencing factors, correlation coefficients and VIF-tests were examined (Statistics Solutions, n.d.). The results are displayed in appendix Ⅲ. As is common within social sciences, the current study treats the Likert-scales as intervals and the underlying variables as continuous, as the scales consists of seven scale points (Laerd Statistics, n.d.).

The aim of H3 was to compare means between the groups in order to determine the possible combined effect of the two independent variables on trust in AI. To this end an ANOVA with Bonferroni correction was conducted, which has become a popular method when conducting experimental research (Armstrong, 2014). As testing of H3 implied simultaneous testing of the scenarios, the Bonferroni correction was deemed suitable as it is one of the most versatile and robust methods to deal with potential multiple test problems which could occur (Darlington & Hayes, 2016).

To test H4-7, the PROCESS-macro developed by Andrew Hayes was employed, which has become the standard approach to moderation analysis (Geuens & De Pelsmacker, 2017). It is also an extension of the linear regression model (Hayes, 2017), suitable to test moderating effects for relationships previously tested using simple linear regression. All variables were mean centered prior to running the moderation analysis (Hayes, 2017). To test H4-6, model 1 in PROCESS was chosen as it allows for one moderating variable. For H7, PROCESS model 2 was used which allowed for the inclusion of the two moderating variables.

To answer our hypotheses, multiple t-tests were examined applying a significance level of 5% (Pyrczak & Oh, 2018). The unstandardized coefficient (β) was interpreted in order to draw conclusions regarding the strength and direction of the relationship between the predictor variable and the dependent (Grace & Bollen, 2005). In addition, For H4, H5 and H6, the significance level of the interaction (Int_1) was assessed to see if there was any interplay between the moderators, independent- and dependent variables (Pyrczak & Oh, 2018).

RESULTS

Descriptive statistics

The sample consisted of 175 respondents (n=175) evenly distributed between the different scenarios. The number of respondents per treatment group indicates sufficient statistical power (Geuens & De Pelsmacker, 2017). The aspect of statistical power was considered highly important to minimize the risk of receiving significant results for non-existing relationships, and not being able to confirm existing effects (type Ⅰ and Ⅱ errors) (Geuens & De Pelsmacker, 2017). 42.4% of the respondents were men and 55.8% women and the mean age of respondents were between 24-25 years old, and the sample was thus representative of the Swedish student population enrolled in higher education (UKÄ, n.d.). In addition, 74,5% of respondents stated to be interested in technology and new tech-related products, comparable to 84% of the Swedish working population being curious about new digital technology (Manpowergroup, 2018). To control for possible differences on trust in AI as a result of both gender and familiarity with technology (e.g. Beldad, de Jong & Steehouder, 2010), these variables were tested in a simple regression model. In the context of our study, both variables were insignificant. As all survey questions were mandatory, there was no missing data to report. To avoid careless or inattentive responses, two main control mechanisms were employed, namely response pattern analysis and response time analysis (Geuens & De Pelsmacker, 2017). The response pattern analysis showed no extreme or notably inattentive answers, after which no outliers were identified. The response time analysis identified a total of 10 outliers across all four scenarios, which were excluded, leaving a data set of 165 respondents.

Manipulation checks

In order to confirm the validity of the two manipulated independent variables, respondents were asked two questions; "Did you perceive the online agent to be transparent regarding collection and use of personal data" (Transparency); and "To what extent did you perceive the party in the chat window as a person?" (Anthropomorphism). Both questions applied a 7-point likert scale, ranging from "not at all" to "very much" and "not at all person-like" to "very person-like" respectively. The results showed significantly different means for both anthropomorphism (low= 2.25, high=2.76, t= -2.367, p=0.019) and transparency (low= 3.41, high=3.92, t=-2.082, p=0.039), confirming the validity of the manipulations.

Checking H1-3: The effect of Anthropomorphism and Transparency on Trust in AI

Testing H1, the results from the regression analysis showed no statistical significance (p=0.352) and the hypothesis was thus not supported. The same test was applied for the proposed relationship between trust and transparency, which was statistically significant (p=0.012, t= -2,554) with a direct negative impact on trust (β= -0.491), supporting H2. The Bonferroni correction method showed no significant differences between the scenarios, and H3 was therefore not supported. See figure 3 for the statistically significant result of H1-3.

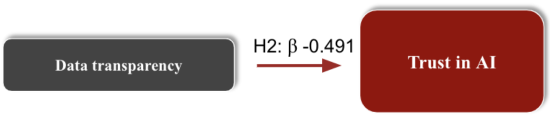

FIGURE 3: The found relationship between the independent variables and the dependent variable in H1-3.

Checking Hypothesis H4-7: The moderating effect of privacy concern and perceived personal relevance on Trust in AI

To test H4, Model 1 in PROCESS was used (Hayes, 2017) which revealed statistical significance for both transparency (p=0.0203, t= -2.3449, β= -0.4165) and privacy concern (p=0.0000, t= -5.5291, β= -0.3287), but there was no significant interaction effect (p=0.8244). The hypothesis was thus not supported. For H5, anthropomorphism was not significant (p=0.3065) reflecting the result of H1. The variable of privacy concern was significant (p=0.0000, t= -5.9365, β= -0.3417). There was no significant interaction effect (p=0.4325). The result indicates that privacy concern is not a moderator, but instead a predictor of trust, with a direct negative effect on trust in AI (Figure 4).

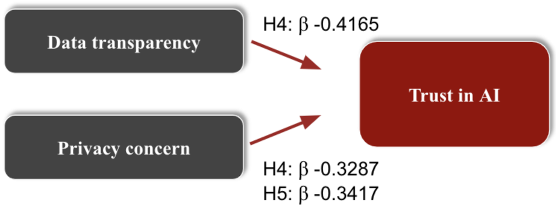

FIGURE 4: The found relationships between the independent variables and the dependent variable in H4-5

Through testing H6 we found that transparency was not significant (p=0.0707) while personal relevance showed a statistically significant impact on trust in AI (p=0.0000, t=13.1047, β=0.6273). No significant interaction effect could be observed (p=0.6635). This implies that personal relevance is not, as hypothesized, moderating the relationship between transparency and trust but instead has a strong direct positive effect on trust in AI. The final test included both moderating variables (H7) on the relationship between transparency and trust in AI, using PROCESS model 2 (Hayes, 2017). The result revealed that personal relevance was significant (p=0.0000, t=11.8690, β=0.5800), as was privacy concern (p=0.0011, t= -3.3342, β= -0.1539. Transparency was not significant (p=0.0802). There were no significant interaction effects (int_1: p=0.8341, int_2: p=0.1934). The hypothesis was not supported. Figure 5 highlights the statistically significant relationships found through statistical testing of H6-7.

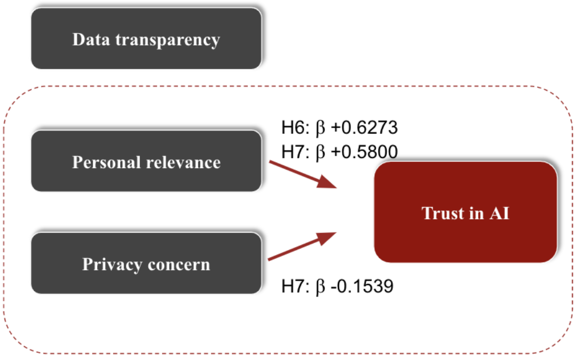

FIGURE 5: The found relationships between the independent variables and the dependent variable in H6-7

In conclusion, statistical testing only provided support for H2 with the current data set, leading to a rejection of the other hypotheses (See table 2). It was found that data transparency, personal relevance and privacy concerns all have direct effects on trust in AI.

Hypotheses	Support
H1: Anthropomorphism has a direct positive effect on trust in AI	No
H2: Data transparency has a direct negative effect on trust in AI	Yes
H3: Anthropomorphism in combination with data transparency will have a stronger effect than only anthropomorphism	No
H4: The effect of data transparency on trust in AI is moderated by the level of privacy concern	No
H5: The effect of anthropomorphism is moderated by the level of privacy concern	No
H6: The effect of data transparency on trust in AI is moderated by personal relevance	No
H7: The moderating effect of privacy concern between data transparency and trust in AI will disappear when introducing personal relevance as an additional moderator	No

TABLE 2: Review of hypotheses

DISCUSSION

Theoretical implications

This study identified several factors to take into consideration when using AI in several stages of an online shopping experience, and its implications on trust. There was no support for H1, that anthropomorphism of an AI agent would positively affect trust. This was in contradiction to previous findings for autonomous vehicles (Hoff & Bashir, 2015; Waytz, Heafner & Epley, 2014; Lee et al., 2015; Ruijten, Terken & Chandramouli, 2018). As automotive automation is arguably more complex than AI-applications in shopping environments, it is possible that for such environments, the notion of human elements proves integral to trust the system in order to surrender control. Such loss of control is not necessarily comparable to an online shopping context. More research is needed to confirm this result.

Previous studies have found anthropomorphic cues can invoke feelings of for instance, satisfaction and pleasure (Verhagen et al., 2014). This is perhaps more applicable to the context of the apparel industry, where anthropomorphic cues may still affect the overall experience positively, in spite of not having a significant effect on trust. As this was not the object of the study, no general conclusions regarding this fact are offered. It is also possible that as machines are expected to perform perfectly (De Visser et al., 2012; Hoff & Bashir, 2015), users do not need the extra comfort possibly provided from a human interface unless something happens which makes them question the functionality of the system. Additional research investigating anthropomorphism of online agents in shopping contexts will be useful and interesting input in this discussion.

Contrary to H1, data transparency showed a significant negative relationship with trust in AI and H2 was thus supported. In other words, explicitly informing users of what information is collected and how this is used to aid them in their shopping experience, seemingly led to users displaying less trust in AI. This is in line with previous research where explicitly stating use of personal information resulted in negative consumer responses (Wattal et al., 2012; Karwatzki et al., 2017; Bauman & Bachmann, 2017). While a previous business study found that trust in AI might be lacking due to insufficient communication (Enkel, 2017), our result suggests that perhaps communication in relation to data collection, is only needed to a certain degree. In our study, the level of data transparency was high and rather detailed, and for this format trust decreased. As such, while previous research has shown that transparency is positively related to trust (Krasnova, Kolesnikova & Günther, 2010), this may be limited to merely stating that information is in fact being collected and used. As consumers are generally unaware of their data being collected (Aguirre et al., 2015), explicitly informing them of both the process and details, as was the case in the current study, may be too much for consumers to process. It is possible that this amount of information may provoke a sense of discomfort or creepiness, leading to a decrease in trust, potentially stemming from a feeling of invasion of privacy (Wattal et al., 2012). Explaining and justifying the decision-making process, is indeed highlighted as one of the most crucial challenges for AI (Rossi, 2019), and stricter demands from both governments and consumers is perhaps to be expected (Morey, Forbath & Schoop, 2015). While explaining why a decision had been made is likely the way forward to promote consumer trust (e.g. Pu, Chen & Hu, 2012; Adadi & Berrada, 2018), perhaps other formats of data transparency than the one tested in the current experiment offer more encouraging results.

The data set did not offer support for H4 and H5, meaning that privacy concern did not moderate either of the two proposed relationships. The testing of both hypotheses confirmed the previous results of H1 and H2, but also revealed a direct negative relationship between privacy concern and trust in AI. While the results were not in line with what was predicted, privacy concern is one of the greatest consumer issues (e.g. Bauman & Bachman, 2017; Wu et al., 2012) and AI is dependent on personal data. Therefore, it is not odd that privacy concern was shown to be a direct predictor of trust in AI. It is likely also a reflection of the general increase in awareness amongst consumers regarding data collection (Morey, Forbath & Schoop, 2015; Cottrill & Thakuriah, 2015). Privacy concern has been shown to both be a predictor of trust (Ermakova et al 2014; Aïmeur, Lawani & Dalkir, 2016, Wu et al., 2012), and a moderator (Taddei & Contena, 2013) and the present results adds to previous findings by including the aspect of AI. The result is also in line with the business studies which identified perceived risks regarding safety and control of data as a reason for not trusting consumer-facing AI (Schierberl, 2019; PWC, 2020).

It is important to note that the variable of privacy concern was to reflect an inherent trait, and questions were posed unrelated to the events in the scenario. For H4 specifically, in contexts which involve data collection, communicated very openly or sparsely (low/ high data transparency), the direct negative relationship found may be a reflection of a reduction in control (Milne & Gordon, 1993; Caudill & Murphy, 2000). For low data transparency scenarios, this could potentially stem from the inability to fully understand the type of personal data collected. For high data transparency, the explicit information may cause concern as there are no ambiguities regarding what is collected. H5 built on the finding that when privacy threats are perceived to be high, online users may prefer to provide information to an anthropomorphic agent (Lee, 2019). The lack of statistical significance for this proposed relationship may simply show that respondents did not perceive such threats or feelings in the environment.

While H6 and H7 were not supported, the result of the two hypotheses highlighted personal relevance as a positive predictor for trust in AI. This is in line with findings that personalization may increase trust for recommender systems (Benbasat, 2006). For H6, the inclusion of personal relevance in the model even affected the previously identified relationship between transparency and trust in AI. This specific effect reveals that as long as the AI-generated advice and aid are perceived as personally relevant, any adverse effect associated with data transparency is no longer significant enough to negatively influence trust in AI. As personal relevance has been shown to positively influence information disclosure online (Zimmer et al., 2010), the result may show that if consumers experience personal relevance of the online encounter, they are less concerned about the explicit data transparency. While somewhat contradictory to previous findings where personalization could have a negative effect on trust due to the aspect of data collection (Bauman & Bachmann, 2017), this study included the concept of personal relevance to better understand personalization effects. It is therefore possible that such a negative effect would be observed if the person encountering a personalized event, did not find the help relevant to them.

The same finding was confirmed when testing H7, where data transparency was no longer a significant predictor of trust in AI. Instead, H7 highlighted previous findings on the hypothesized moderating variables, namely a direct negative (privacy concern) and a direct positive (personal relevance) relationship with trust in AI. Looking at β for privacy concern in testing H4, H5 and H7, the results indicate that when including personal relevance in the model, the negative relationship between privacy concern and trust in AI is less strong. This would indicate that personal relevance has an attenuating effect on individual privacy concerns. While more testing regarding this conclusion is necessary to confirm any results, this would be in line with findings that consumers may disregard any privacy concern as long as they find the personalization beneficial (e.g. McDonald and Cranor 2010; Ur et al, 2012). As trust in AI differs across industries (Schierberl, 2019; PEGA, 2019), the analysis does not extend to cover other categories of consumer goods outside of the apparel industry. However, it is possible that the results are transferable for other consumer goods categories which are similar in terms of effort, involvement and risk evaluation. Examples of these could be the shoes segment, accessory or beauty industry, which are all part of consumer goods.

Managerial implications

Consumer trust in AI technologies has been identified as one of the greatest challenges to improving the online customer journey (PWC, 2020), for which this study offers some interesting findings. For marketers, the results regarding personal relevance highlights the potential of using AI to deliver personalized content and advice to their customers. If there would be increasing demands for more data transparency, the results indicate that it will likely not harm trust as long as they succeed in keeping the content personally relevant, in line with findings by Kim & Huh (2017).

Investing in personalization processes may thus be one way to both optimize data processing and targeting efforts, and ensure the company is equipped to tackle possible changes concerning data transparency. It is important to note that the analysis regarding the concept of personal relevance, was built on the authors' assumption that there is a connection between successful personalization and subsequent consumer evaluations regarding personal relevance. As such, the result regarding the negative relationship between data transparency and trust should not be overlooked. For instance, if the personalization aspect is not perceived as successful, it could still pose a problem. Therefore, it is important to not only personalize content to the best of a company's capabilities and resources, but to follow up with consumers regarding how they experienced the help and adjust the marketing strategy accordingly. This suggestion is closely related to the personalization privacy paradox, where a balance of party objectives is key for its success (Awad & Krishnan, 2006, Karwatzki et al., 2017).

It is also important to note the aspect of ethical behavior in discussions regarding the use of consumer facing AI. As authors, we encourage companies to be reflexive in their marketing strategies, and consider the integrity of consumers in every step. For instance, while it may be possible to identify consumers who are more prone to experience privacy concerns and adjust marketing efforts and content accordingly, this could be considered ethically questionable. Instead companies should explore possible avenues to alleviate such consumer concerns.

LIMITATIONS

While the study demonstrated several interesting relationships, there are some limitations to discuss. First, as experiments allow for strong manipulations in controlled environments (Söderlund, 2018), it is likely that these elements are not as protruding in reality. Second, while students may be argued to provide an adequate sample to explore a phenomenon (Henrich, Heine & Norenzayan, 2010) it is possible that the results at hand are not generalizable to the general online consumer. Lastly, we tried to reflect the possible influencing factor of having confidence in machines and one's technical capabilities with the control-variable," tech-savvy". It is possible however, that we did not capture this specific effect as one may be interested in technology without having confidence in it.

DIRECTIONS FOR FUTURE RESEARCH

The present research sought to explore both anthropomorphism and transparency in relation to consumer trust in AI, for which the current sample consisting of university students offers interesting insights into this phenomenon. For future research endeavors, replications of the current study in the apparel industry, and in different cultural contexts and across different populations is needed to confirm the research result at hand. Especially interesting would be to investigate further into the non-existent relationship between anthropomorphism and trust, as it contradicts much of the existing literature (e.g. Waytz, Heafner & Epley, 2014). In addition, the current way of using and applying the term of data transparency, contributes to the scarce field on this kind of information transparency.

As many companies operate in global environments and have to conform to a multitude of regulatory frameworks, it is possible that companies will have to be increasingly transparent with online users regarding what type of information they collect (Morey, Forbath & Schoop, 2015). As the research at hand found indications that consumer trust diminishes with increasing data transparency, future research should explore different formats to present this to online consumers without harming the trust-formation process. In addition, the strong direct effect between personal relevance and trust in AI highlighted the potential upsides of successful personalization efforts. It would also be interesting to examine possible risks which might moderate this positive relationship, such as privacy breaches or explicit/ implicit information regarding the employment of AI. The latter may be of special interest as consumers who distrust AI may not be aware that they are using the automated system in other parts of their life (PEGA, 2019).

CONCLUSION & CONTRIBUTION

Our study explored factors which determine consumer trust in AI, and possible opportunities and challenges related to this. To answer our first research question, we found *personal relevance* was a positive predictor of trust in AI, and *data transparency* and *privacy concern* were both found to be negative predictors of trust in AI. When including all three determinants, the results also showed that data transparency was no longer a significant predictor.

To answer our second research question, personal relevance was identified as the main opportunity related to trust in AI. One of the main challenges identified was privacy concern, and is likely difficult to deal with as it is often an inherent trait. The finding on data transparency does pose a challenge if companies need to increase transparency, but also an opportunity to find a format which does not affect trust as the format tested in this study did.

The study thus contributes to the scarce field of trust for consumer-facing AI technologies in the apparel industry, and trust in the setting of web 3.0. It also highlights the important dimension of personal relevance, which may be an interesting avenue for future research endeavors. By including previous findings on trust in AI for other industries, we also found that trust determinants are likely to differ between them. Specifically, the aspect of anthropomorphism of an automated system was not a determinant for trust in this study.

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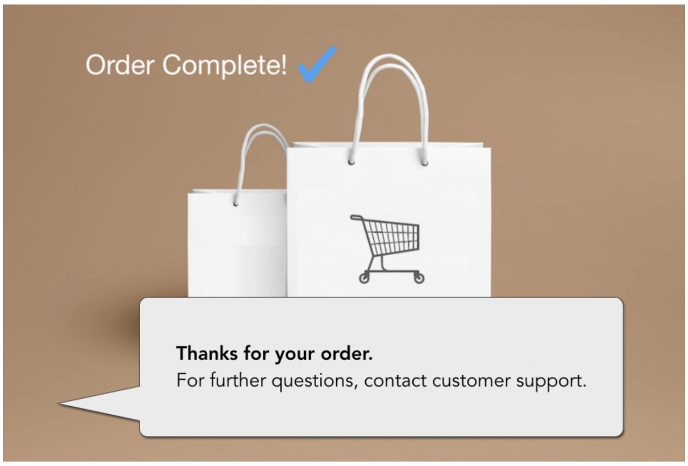
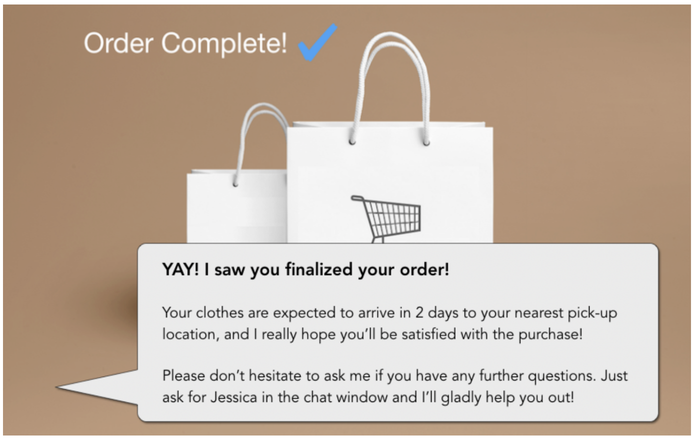
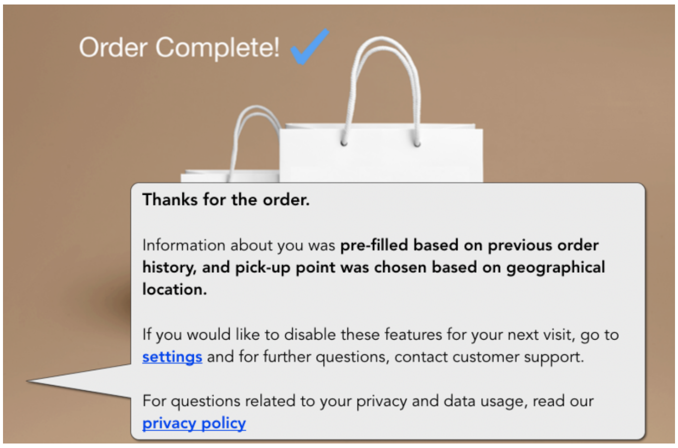
Appendix Ⅰ - Treatment examples



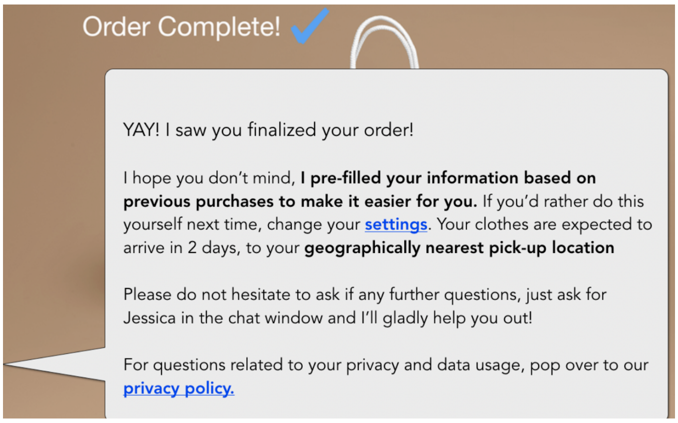
Scenario 1: Anthropomorphism low, Data transparency low



Scenario 2: Anthropomorphism high, Data transparency low



Scenario 3: Anthropomorphism low, Data transparency high



Scenario 4: Anthropomorphism high, Data transparency high

Appendix Ⅱ- Scale items

Scales	Items	Sources
Measured on 7-point scales		
Trust *"I believe the overall online experience was…"*	Credible Reliable Clear Useful Likeable Enjoyable Positive	Soh, Reid & King (2009); Lee et al. (2015)
Privacy concern	*It usually bothers me when some websites ask me for personal information.* *When websites ask me for personal information, I sometimes think twice before providing it.* *It bothers me to give personal information to so many websites.* *I'm concerned that websites are collecting too much personal information about me*	Smith, Milberg & Burke (1996); Bellman et al. (2004)
Perceived personal relevance	*The personalized advice and communication was useful* *The personalized advice and communication was important* *The personalized advice and communication was meaningful* *The personalized advice and communication was helpful*	Mishra, Umesh & Stem (1993); Zimmer et al. (2010)

Appendix Ⅲ- Multicollinearity test

Correlations

		Humancues	Transp
Humancues	Pearson Correlation	1	.006
	Sig. (2-tailed)		.942
	N	165	165
Transp	Pearson Correlation	.006	1
	Sig. (2-tailed)	.942	
	N	165	165

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	4.878	.420		11.614	.000		
	Transp	-.490	.192	-.196	-2.548	.012	1.000	1.000
	Humancues	-.179	.192	-.072	-.934	.352	1.000	1.000

a. Dependent Variable: Trust