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Consumer intentions towards AI in the healthcare industry

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

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Abstract

Two major challenges for the healthcare industry are to reduce misdiagnosis of patients and to become more efficient in everyday practice. The lack of efficiency became extremely apparent by the pressure on healthcare workers caused by the COVID-19 pandemic. This could be assisted with new technologies. Artificial intelligence (AI) is one technological development that has the potential of improving healthcare by overcoming these two challenges. Hence, more research on AI in healthcare is essential. To successfully implement AI in healthcare it is vital to understand what positively influences individuals to accept and utilise AI in healthcare. Therefore, the present study investigates the following research question: *What factors influence consumers' intention to accept AI within healthcare?* Seven potential factors are tested to either directly or indirectly affect consumer intentions. Attitudes and trust are hypothesised to have a direct effect, perceived usefulness is hypothesised to have a direct as well as an indirect effect, and perceived knowledge, anthropomorphism, data transparency, and privacy concerns are hypothesised to have an indirect effect. The purpose of this study is to find out which of these factors have the highest influence on consumer intention to successfully implement a future AI healthcare service.

This topic is investigated through a quantitative method with nine hypotheses based on previous literature and theoretical frameworks. A questionnaire was designed and distributed to students at the School of Business, Economics and Law at Gothenburg University to collect data. The analysis supports all hypotheses, except for hypotheses 8 and 9 concerning data transparency and privacy concerns. Further, the proposed research model has a good fit and is consistent with the data as well as in line with previous theories.

Perceived usefulness was shown to be the strongest predictor of consumer intention, followed by consumer attitudes. Furthermore, perceived usefulness was the strongest predictor of attitudes, meaning that perceived usefulness additionally affected consumer intention through a mediating variable. Anthropomorphism is the strongest predictor to trust, also affecting consumer intentions indirectly through a mediating variable. Therefore, the mentioned factors are the ones that should be focused on when aiming to increase consumer intention regarding AI-based healthcare.

The present thesis contributes to research on the utilisation of AI within healthcare from a consumer perspective, which is an area where there is opportunity for further exploration. By focusing on the predictors in the proposed model consumer intentions to utilise AI in healthcare can be increased.

Keywords: Artificial Intelligence (AI), consumer behaviour, intentions, attitude, trust, perceived usefulness, perceived knowledge, anthropomorphism, privacy concerns, data transparency

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1. Introduction

According to the World Health Organization (n.d.), 23% of the people living in countries of the European Union state that they have experienced direct effects from medical errors in connection to healthcare. In Sweden, the percentage of serious injuries in healthcare caused by diagnostic errors such as misdiagnosis is 10–20% (Sveriges Kommuner och Regioner, 2021). Graber et al. (2018) affirm that healthcare must perform better within this area since errors in diagnosis are costly regarding both money and the health of individuals. In addition, 90% of the world's countries in April 2021 continued to experience health services being disrupted due to the COVID-19 pandemic (World Health Organization, 2021). Achieving both efficiency and quality within healthcare is an issue that must be improved (Graber et al., 2018). These two challenges could be aided with the help of novel technologies (Guo & Li, 2018; van Leeuwen et al., 2021).

Such a novel technology that has made an entrance in the new technological revolution is *artificial intelligence*, or AI (Zhu & Sun, 2021). Several people further believe that AI has the possibility of being more intelligent than human experts in many fields (Jarrahi, 2018). AI has been defined as various techniques (e.g., machine learning, pattern recognition, etc.) which are made to happen by a computer/machine with the ability to perform tasks that are intelligent by human standards and do so without human interference (Esmaeilzadeh, 2020). The term will be used in this study as intelligent machines with the capability of behaving and interacting in a human-like way, with little to no human interaction.

Vaishya et al. (2020) connect the global pandemic crisis of COVID-19 to the possible usage of AI. AI could improve the situation by monitoring patients and controlling the spread of infection (ibid). Additionally, other potential areas of AI usage within healthcare are patient diagnosis, medical predictions, locating tumours, and surgery (Davenport & Kalakota, 2019; O'Sullivan et al., 2019). On the other hand, a type of usage within healthcare services is AI chatbots, which can automatically engage in conversations with patients (Nadarzynski et al., 2019).

Yun et al. (2021) researched both intention and attitude and wrote about consumer responses to AI versus humans providing medical services. Yun et al. (2021) concluded that it would not be realistic to replace human healthcare professionals with AI in the near future due to the respondents not being ready for such technological development. However, it was suggested for future research to study the different effects of various illnesses within the same context, i.e. what the severity/type of illness does to a patient's/consumer's perception of AI in healthcare (ibid). Therefore, first healthcare check-ups (typically with lighter symptoms) are an area that is theorised to possibly benefit from the use of AI.

From a consumer perspective, one important question is if consumers will embrace a change in healthcare with AI. Little research exists within this area and further studies are needed to understand and predict consumer behaviour in relation to AI within this context (Abrardi et al., 2021). Finding out what would increase the will of consumers to utilise AI in healthcare would therefore be vital for future implementation of AI services in the area of healthcare.

Therefore, this study focuses on consumer intentions to accept AI in healthcare, specifically within the first check-up for a patient with light symptoms. Hence, the following research question is posed:

- *What factors influence consumers' intention to accept AI within healthcare?*

The tested relationships are based on previous theories and findings and include attitudes, trust, perceived usefulness, perceived knowledge, anthropomorphism, data transparency, and privacy concerns. The study is further based on the theory of planned behaviour and the technology acceptance model with an overall focus on the healthcare industry from a consumer perspective.

The purpose of this study is to gain a broader knowledge of consumers' intention to accept AI within healthcare to help with successfully implementing such a service. Further, to identify which of the tested factors are the most important for consumers' intention to accept the use of AI within healthcare. The findings will provide essential information necessary for such implementation.

2. Theoretical framework

In this chapter, a review of the theories and models on which the present study bases its hypotheses will be presented.

2.1 Theory of planned behaviour

The *theory of planned behaviour* (TPB) describes how different factors can influence and explain how people behave and how people make choices (Ajzen, 1991). Human behaviour has been highlighted to be a complex interplay of various components, which are challenging to explain (ibid). Therefore, finding influencing factors to human behaviour should be of high interest.

TPB consists of a central factor, the intention individuals have to perform a certain behaviour (Ajzen, 1991). Further, TPB is built up of three independent predictors of intention: attitudes, subjective norms, and perceived behaviour control, see Figure 1 (ibid). Attitude regarding the behaviour concerns an individual's evaluation of the behaviour (Ajzen, 1991).). This evaluation may consist of positive, negative, or mixed feelings towards the behaviour (ibid). Subjective norm is a social element that concerns the social pressure that a person may perceive concerning the performance of the action (Ajzen, 1991).). Perceived behaviour control, the last component of the theory of planned behaviour, concerns the perceived difficulty or ease of acting on the behaviour (ibid). Ajzen (1991) expresses that a person's intentions increase when the attitude and subjective norm are more favourable, and when the perceived behaviour control is greater. However, Ajzen (1991) highlights that in some situations and behaviours, the different predictors may have different importance.

As mentioned above, TPB explains how different factors influence individuals' intentions to perform a specific behaviour in a general perspective (Ajzen, 1991). The purpose of this present study is to gain a broader knowledge of what influences individuals' intentions, therefore, this research is partly based on this theory.

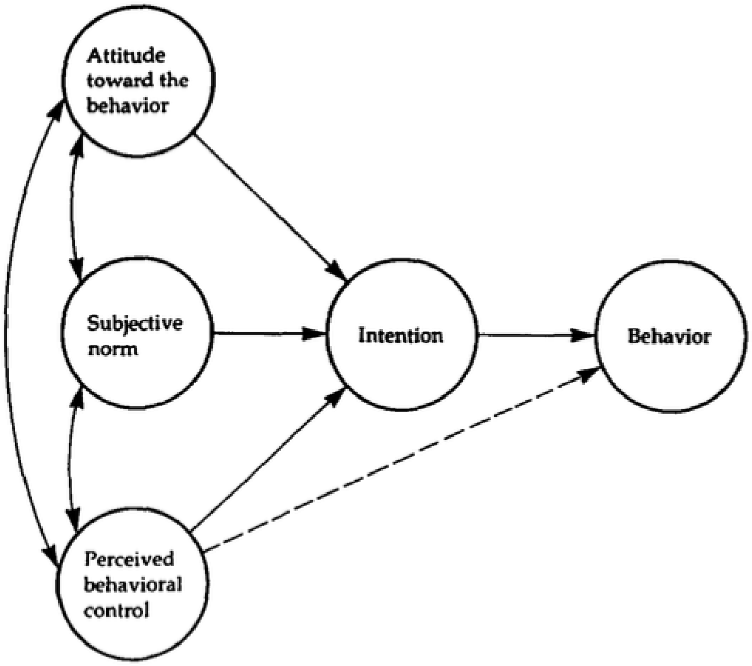

Figure 1: TPB model, as illustrated by Ajzen (1991, p 182).

2.2 Technology Acceptance Model

The *technology acceptance model* (TAM) explains how different factors influence individuals' intentions and behaviour when accepting new technology (Choe et al., 2021). Previous research has combined TPB and TAM when studying consumer intentions and the context of new technology as well as in marketing strategy (ibid). As previously mentioned, TPB has the downside of being general as a model and does not include new technologies when looking at consumer intentions, making the combination of the two models suitable for a context with both consumer intentions and technological advancements (Choe et al., 2021).

When technology is making progress in society and becoming a part of consumers' day to day activities, deciding whether to accept it or not is a crucial issue (Marangunić & Granić, 2015). TAM is applied in many contexts (King & He, 2006) and is prevalent in technology acceptance research and has been proven to be a vital model to use when setting out to make sense of human behaviour when rejecting or accepting technology (Marangunić & Granić, 2015). Davis et al. (1989) mean that TAM is a widely utilised model for foreseeing factors that can influence consumer adoption of novel technologies.

The foundation of TAM is that attitude toward technology is affected by a person's way of thinking and understanding of technology (Lee & Kim, 2009). According to the model, perceived usefulness and perceived ease of use determine an individual's behavioural intention (Marangunić & Granić, 2015). Jokar et al. (2017) go on to explain that the TAM is built up of the following parts: use, attitude, perceived ease of use, and perceived usefulness, see Figure 2.

Previous research has applied TAM in the context of healthcare, technology, and innovations/concepts (e.g., Jokar et al., 2017; Kamal et al., 2020) and the present study examines individuals' intentions from a consumer perspective with a technological and healthcare context, TAM is considered an appropriate model to utilise for the research objective of the present study.

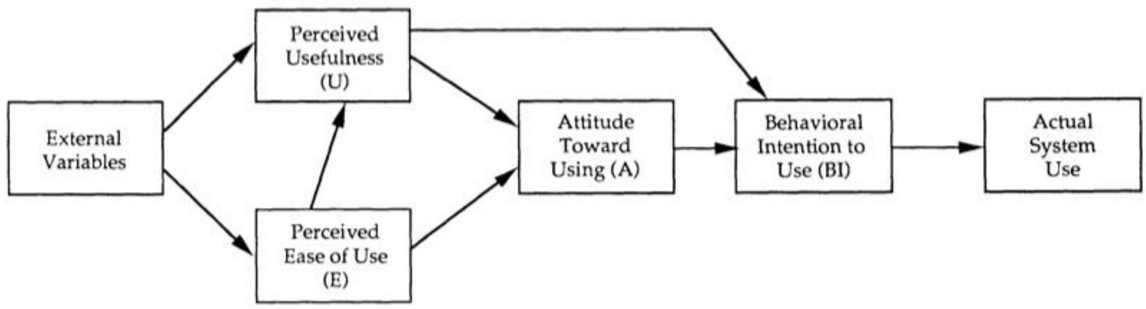

Figure 2: As illustrated by Davis et al. (1989, p. 985).

3. Literature review and hypotheses development

The following section serves to develop hypotheses based on supporting literature and theories. The hypotheses are presented in an analytical model, see Figure 3.

3.1 Intentions

While previous research has focused more widely on individuals' intentions to adapt to new technology, little research has focused on individuals' intentions to adapt to AI within a healthcare context (Zhu & Sun, 2021). AI has been shown to positively influence efficiency and productivity for organisations in various contexts (ibid).

Intentions have been described by Sheeran (2002) as the plan and the instructions that an individual gives to oneself with a goal that aims to result in a specific outcome. Intentions further include a person's strength and direction of the intended action, as well as one's motivation to act on the behaviour (Sheeran, 2002). According to Ajzen (1991), intentions concern the probability of the action taking place and the effort an individual plans to exert.

Ajzen (1991) further highlights that intention and behaviour have a positive correlation, meaning that when intentions are stronger, the possibility of the behaviour happening increases.

In the present study, intentions refer to an individual's plan and the instructions that the person gives to oneself to consider and use AI in the first contact with healthcare. In this case, "first contact with healthcare" refers to the first consultation that a doctor usually does to give a treatment plan or health advice.

Zhu and Sun (2021) highlight that previous studies have focused more on clinical results and technical innovation rather than the ethical challenges which occur when AI and individuals interact. Zhu and Sun (2021) further stress that it is crucial to make sure real-world issues are assessed before implementing a tool. These issues and challenges could be individuals' concerns to accept AI, how to protect their privacy to trust the tool, their attitudes towards AI, and what influences their attitudes (ibid). It is vital to understand what affects peoples' intention to adapt and their acceptance of AI in healthcare (Zhu & Sun, 2021). With the right knowledge, individuals' concerns will decrease and help hospitals make the right regulations to use AI effectively (ibid).

Zhu and Sun (2021) state that it is crucial to find the predictors that influence consumers' intentions and acceptance. Previous literature has shown that consumers' attitudes towards AI are closely linked to how they will accept and use the technology in their daily lives. Further trust in the consumption of technology and AI has shown to have a positive influence on consumer intentions as well as feeling that the outcome of using AI results in higher relative advantage compared to other potential options (Gefen et al. 2003; Zhu & Sun, 2021).

In a marketing context, Morwitz (2014) highlights that marketing managers frequently measure consumer intentions as a key to help decisions regarding existing and new products and services. This should mean that knowing which predictors influence consumer intentions should further help marketing managers to implement and market AI in the healthcare industry. There is no previous literature that investigates these predictors affecting consumers' intentions to adopt AI in healthcare (Zhu & Sun, 2021). This further means that there is no previous literature that has studied predictors affecting consumers' intention to adapt to AI in the case of a first check-up with light symptoms.

3.2 Attitudes

Previous literature has shown that attitudes towards AI have been a significant predictor of consumer intentions to adapt to AI (Zhu & Sun, 2021). On the other hand, Scott et al. (2021) note that research concerning attitudes towards AI within healthcare is minimal.

Attitudes have been defined as the evaluation an individual makes concerning a specific object (Ajzen, 1991). These evaluations are based on behavioural, cognitive, and affective information (Eagly & Chaiken, 2007), and are negative or positive, but can also be of mixed feelings (Ajzen, 1991). Eagly and Chaiken (2007) explain that anything that can be held in mind and discriminable, both of conscious awareness and below, can be evaluated and be an attitude object. Previous research has identified attitudes to be one of the most significant variables predicting a person's intentions concerning a specific object (Rucker & Petty, 2006).

A previous study by Swan (2021) focusing on the knowledge and attitudes of nurses about AI showed that 70% of the respondents believed that AI will help and support disease prevention, health promotion, automating routine tasks, and making administrative tasks faster. Scott et al. (2021) studied different stakeholders' attitudes toward AI in clinical practices and received different results where healthcare consumers perceived AI within healthcare to be more favourable than other individuals. In conclusion, the respondents in the study had a positive attitude towards AI within healthcare (Scott et al., 2021).

Gessl et al. (2019) concluded in their study that ambivalent attitudes are common when it comes to valuable technology. In the continuously changing world, distrust arises when facing unpredictability which has become a part of life (Swift et al., 2014). Destephe et al. (2015) pinpoint that mixed feelings are common when individuals come into contact with AI. Feelings like excitement, curiosity, anxiety, and importance are common (Edelman Agency, 2019). Acemoglu and Restrepo (2020) further highlight the increased concerns regarding the reduction of jobs that may be caused by AI. On the other hand, Zhang and Dafoe (2019) stress that it is vital to understand technological solutions because they can improve individuals' well-being and everyday lives.

Lennox-Chhugani et al. (2021) state that attitudes towards the use of AI in healthcare are improving, individuals feel positive about AI supporting diagnosis, but they want humans to be involved. Lennox-Chhugani et al. (2021) further concluded in their study about attitudes toward AI in breast cancer screening that woman are open to using AI as well as have mixed feelings regarding the subject and are uncertain if AI can be trusted. It is therefore important to understand individuals' attitudes toward AI in healthcare to strengthen individuals' adoption and acceptance of AI technology (Lennox-Chhugani et al., 2021).

A better understanding of consumer attitudes is one important aspect to predict consumer intentions (Ajzen, 1991). This can further help how to implement and market AI technology (Persson et al., 2021).

Previous research has identified attitudes to be a significant predictor of consumer intentions. Based on this and the theory of planned behaviour the following hypothesis is proposed:

H1: Positive attitudes toward AI have a positive effect on consumer intention toward AI in the first contact with healthcare.

3.3 Trust

Trust is important in every relationship (Montague, 2010). Commonly, two parties exist in the presence of trust, one party is concerned about the other while the trusting party is in a vulnerable position (Bauman & Bachmann, 2017). Trust has been explained as a human belief (Lee & See, 2004) based on three dimensions; integrity, benevolence, and ability (Mayer et al., 1995; Mcknight & Chervany, 2001; Chen & Dhillon, 2003). Trust may further be based on an individual's past experiences, interests, knowledge, and the reputation of the subject (Han et al., 2013).

Asan et al. (2020) state that trust is the most important variable when predicting consumer intention in the relationship between people and AI. Even more important in the context of healthcare where there is a matter of life and death (ibid). Zhu and Sun (2021) claim that patients will only be willing to accept and adapt to AI if they feel like the technology can be trusted. Trust provides a feeling of safety and satisfaction as well as reduces individuals' perceived uncertainty (Zhu & Sun, 2021; Asan et al., 2020). Asan et al. (2020) pinpoint that lack of trust in AI has a negative significance in the adoption of AI in healthcare. Consumer trust can be positively influenced by education, user biases, past experiences, and perception regarding automation (ibid). Other important factors include transparency, controllability, risk, complexity, privacy etc. (Asan et al., 2020).

Previous scholars have found trust, with the TAM model, to be a significant predictor of consumer acceptance behaviour of different systems (Liu & Tao, 2022). It has further been shown to be highly critical at the beginning of the relationship between humans and AI (Ostrom et al., 2019). Zhu and Sun (2021) found in their study about AI adoption intentions among healthcare patients that trust towards AI has a significant effect on AI adoption intention. Additional research has proved that trust in technology positively influences consumer intention (Gefen et al. 2003; Lee & See, 2004). It has been shown that potential consumers must engender trust to conquer perceptions of uncertainty and risk to accept technological services (McKnight et al., 2002; Zhang et al., 2019).

As previously mentioned, trust in AI has been shown to increase individuals' AI adoption intention in different contexts of healthcare. Therefore, the following hypothesis is proposed:

H2: Higher trust in AI has a positive effect on consumer intention toward AI in the first contact with healthcare.

3.4 Perceived usefulness

According to Davis (1989) perceived usefulness is directly linked to attitude and intention, according to the TAM model. Therefore, a consumer's personal belief on the usefulness of technology influences their attitude towards the technology, while having an effect on the intention to use the technology, which the TAM model illustrates.

Davis (1989) studied subjective measures in technology acceptance, perceived usefulness is defined by him as “the degree to which a person believes that using a particular system would enhance his or her job performance” (p.320). In relation to the TAM model and technology adoption, perceived usefulness has been referred to as consumers’ perception of the outcome of an experience and whether they perceive the new technology to improve that experience (Davis et al., 1992; Davis, 1993). In line with Davis (1989) in the present study perceived usefulness is referred to the degree a consumer believes accepting AI in the first contact with healthcare will improve their experience. Improvements, in this case, could include time saved, accuracy, convenience, equality, and cost-efficiency, as suggested by Sunarti et al. (2021).

Previous literature has proven higher perceived usefulness to influence intention to accept information technology positively, as someone who sees information technology to be useful is more likely to accept it (Davis, 1989; Lee & Wan, 2010). In previous studies within healthcare, it has been seen that perceived benefits significantly influence intention, because if consumers perceive a service as highly useful they are more likely to use the service (Lennox-Chhugani et al., 2021; Esmaeilzadeh, 2020).

As previously described, the perceived usefulness of technology has been seen to affect consumer intentions toward the consumption of technology. Based on this and the Technology Acceptance Model, the following hypothesis is proposed in the context of AI:

H3: Higher perceived usefulness regarding AI has a positive effect on consumer intentions toward AI in the first contact with healthcare.

Further, Upadhyay et al. (2018) found, in the context of sales technology usage, that perceived usefulness directly influences attitude. It has been shown that, within the healthcare industry, AI has been shown to be perceived in a better light (Scott et al., 2021; Lennox-Chhugani et al., 2021). This is when AI can provide improved effectiveness and productivity in a particular activity, thus making the experience better (Scott et al., 2021; Lennox-Chhugani et al., 2021). For example, Lennox-Chugani et al., (2021) found perceived benefits in the implementation of AI in breast screening, even though they did not have positive views on AI’s effect on society, thus had a positive attitude towards AI in breast screening due to higher perceived usefulness.

As explained earlier, the perceived usefulness of technology has been seen to affect attitudes toward technology. From this and the Technology Acceptance Model, the following hypothesis is proposed in the context of AI:

H4: Higher perceived usefulness regarding AI has a positive effect on attitudes toward AI.

3.5 Perceived knowledge

Brucks (1985) divides knowledge into subjective and objective knowledge and further highlights that it has been recognized that knowledge can be derived from previous experiences and familiarity. Familiarity is defined to include personal knowledge and experience with a product, object, or activity, thus being a part of subjective knowledge (DeJoy, 1999). Lee and Wan (2010) on the other hand, state that familiarity is based on awareness of the process and its procedures. In this present study, due to the intangibility of AI, the focus is on perceived knowledge. Perceived knowledge is an individual's self-assessment or feeling of their knowledge of a subject (Park et al., 1987). This according to Brucks (1985) is a part of subjective knowledge as it is how consumers perceive their knowledge of a subject. Therefore, the definition of perceived knowledge used in this present study is the perceived level of knowledge about AI, including previous experiences and learned information about AI.

Previous literature has proven that consumer knowledge has an influence on the technology adoption process (Gatignon & Robertson, 1985; Moreau et al., 2001). Therefore, people with more knowledge about technology are more likely to adopt it, this is due to higher trust and attitude toward the adoptable technology (Gatignon & Robertson, 1985; Moreau et al., 2001). In addition, in the context of autonomous vehicles, Smith (2018) stated that consumers who have higher knowledge about the technology and are more familiar with it are more likely to have a positive attitude towards the usage of AI. Persson et al. (2021) also stated a trend between knowledge and attitude towards AI in their cross-cultural study on attitudes towards AI between Sweden and Japan.

As previously explained, perceived knowledge about AI has an effect on attitudes towards AI. Therefore, the following hypothesis is proposed:

H5: Higher perceived knowledge regarding AI has a significant positive effect on attitudes towards AI.

Gillespie et al. (2021) found that people who feel that they understand and have more knowledge about AI are more likely to trust and accept the usage of AI. In a marketing context within brand knowledge, familiarity and knowledge of a brand create opinions and bias, as it has been seen that perceived knowledge positively influences attitude and trust in brands, products, and services, thus making consumers act favourably towards it (Keller, 1993; Keller, 2003).

As mentioned earlier, perceived knowledge has an effect on trust in the context of AI. Therefore, the following hypothesis is proposed:

H6: Higher perceived knowledge regarding AI has a positive influence on trust in AI.

3.6 Anthropomorphism

According to Epley et al. (2008) the human basic need for social connection has led to the creation of anthropomorphism. Anthropomorphism is the attribution of human-like characteristics to nonhuman agents, which is common for consumers as well as creating social expectations of nonhuman agents (Epley et al., 2007; Troshani et al., 2021; Nass & Moon, 2000). When interacting with machines humans have the expectations of perfect performance, however, anthropomorphism allows the implementation of human-like characteristics or behaviour in non-human agents, such as emotion, self-consciousness, and personality (Lee et al., 2015; Gursoy et al., 2019). In the present study, anthropomorphism is referred to as the level of perceived human-like characteristics in AI-powered healthcare services.

Anthropomorphism is considered a characteristic that distinguishes AI from non-AI technology (Troshani et al., 2021). It has been stated that people prefer receiving healthcare advice from people rather than from robots as consumers may be sceptical about having an algorithm taking care of them instead of a person (Drouin & Freeman, 2020; Longoni & Morewedge, 2019). In a previous study on healthcare service quality, it has been seen that the three characteristics reliability, trustworthiness, and assurance were the most important to consumers, as well as empathy (Singh & Prasher, 2017). Pelau et al. (2021) demonstrate through their findings that interaction quality, as well as empathy, have an impact on whether an anthropomorphic character is accepted. I.e. an AI device which appears more like a human is more accepted if it can demonstrate empathy and interact with the consumer in question (ibid). Therefore, adding human-like characteristics to AI may positively influence trust.

However, some studies have resulted in negative results due to the human-like features of an AI device becoming too overwhelming and uneasy feeling or due to posing a threat to consumers' human identity (Lu et al., 2019; Mori et al., 2012). Therefore, previous literature has shown mixed results (Liu & Tao, 2022; Troshani et al., 2021; Ruijten et al., 2018).

A previous study on trust in AI in services by Troshani et al. (2021) states that anthropomorphism is positively related to trust in AI together with another human-like characteristic of intelligence. In addition, Ruijten et al. (2018) found that adding human-like characteristics to an intelligent user interface increased trust in the technology. However, it has been suggested for the level of anthropomorphism to be allowed to vary, as different services may benefit from higher levels than others (Troshani et al., 2021). These include healthcare services, which may require higher amounts of anthropomorphism, thus also having a positive relationship with trust (Troshani et al., 2021; Wickramasinghe et al., 2016).

In a marketing context, it has been seen for anthropomorphism to humanise brands and companies, which can be extended to a company using anthropomorphism in their AI. In a study on hospitality, anthropomorphism was found to be a useful strategy for communication and advertising (Lee & Oh, 2021). The same authors also state that anthropomorphism can cause higher trust for a brand, because of perceived likeness to humans (Lee & Oh (2021) in reference to Chandler & Schwarz (2010)).

As mentioned above, anthropomorphism has been shown to positively influence consumer trust. Therefore, the following hypothesis is being proposed:

H7: Anthropomorphism in AI positively influences trust in AI.

3.7 Data transparency

Information can be sold, Walker (2016) states. According to Bertino et al. (2019), due to the presence of data in individuals' lives, there is a need for transparency.

A definition of data transparency provided by Bertino et al. (2019, p. 21) reads as follows: "the ability of subjects to effectively gain access to all information related to data used in the processes and decisions that affect them". This particular definition then assumes that decisions that are made based on data in turn have an impact on the individual that has provided the data in question (ibid).

The field of healthcare possesses vast quantities of data, which are now becoming increasingly digital (Raghupathi & Raghupathi, 2014). Xiao et al. (2016) highlight that healthcare intelligence can be gained from healthcare data. This data can further be used to provide intelligence to the service of healthcare, but since this patient data is personal it should be handled with respect to individual privacy (ibid). Bertino et al. (2019) add that data transparency within the medical area most often is about informed consent which is only one section of data transparency. Individuals are worried about what purposes their online data is gathered and utilised and the authors also link transparency in data collection to increased trust (Morey et al., 2015). Consumer data is now vital to the marketing field, but despite this, the way that the transparency of it is being used, as well as trust, is not fully matching the development of technology and information we now experience (Walker, 2016).

Data transparency has gained importance, especially in relation to AI (Felzmann et al., 2019). Since AI makes decisions without human intervention, as previously mentioned, more and more consumers want to know how data is being handled (ibid). Further AI technology needs extensive quantities of, often personal, data to function (Rossi, 2018). Felzmann et al. also bring up the European GDPR law which states that a relation "between transparency, lawfulness, and fairness" (2019, p. 2) exists. Bertino et al. (2019) add that data transparency is crucial for affected individuals to receive the required information to evaluate how useful and impactful the data is, as well as the decisions and results which come from said data.

Nati (2018) writes that increased transparency with consumers in data collection causes a rise in trust. Consequently, consumers would become more inclined to give out information (Nati (2018). A study on consumer trust and data transparency for the company 23andMe by Raz et al. (2020), finds that for many of the respondents' little transparency leads to diminished trust. Connecting this to AI, previous research by Rossi (2018) explains that trust in those producing AI is acquired when firms are being transparent and show consumers how their data is utilised.

As previously mentioned, data transparency has shown to positively influence consumer trust, therefore the following hypothesis is proposed:

H8: Higher degree of data transparency has a positive influence on trust in AI.

3.8 Privacy concerns

Previous research has investigated healthcare and new technologies, connecting the two to privacy concerns and trust (Dhagarra et al., 2020). Rahim et al. (2013) add that the healthcare service industry handles private information in the form of electronic healthcare records (EHR), thus making personal security and managing patient privacy concerns a priority. The same authors found through their study that computer literacy and the spreading of information are factors which cause privacy concerns within healthcare (ibid). Investigating cloud-based systems within healthcare, Sajid and Abbas (2016) emphasise how crucial it is to alleviate patient privacy concerns regarding sensitive personal healthcare information and data.

Yun et al. define privacy concerns as "the concern that individuals have with the information privacy practices of organisations, which could compromise the individuals' ability to control personal information" (2019, p. 570). In the field of marketing, privacy concerns have proven to be an issue for consumers (Bleier et al., 2020). Since marketing benefits greatly from consumer data to do business, questions and concerns around its usage would be of importance both for the individual consumer as well as for companies behind the marketing efforts (Bleier et al., 2020).

Firms misusing or violating agreements about the usage of information which they have been trusted with can cause consumers to mistrust the entity that was given said information (Ayaburi & Treku, 2020). AI is also a field where regulations have difficulty keeping up and ensuring the privacy of consumers (Carmody et al., 2021). Cardon et al. (2021) bring up privacy concerns in relation to AI in business meetings, meaning that a key tension is privacy versus transparency. The notion of tools using AI brings forward questions about control, priv acy and psychological safety (ibid).

Additionally, a significant link between privacy policy content and concern for privacy/trust was found by Wu et al. (2012). Bansal et al. (2016) also state that trust has an important relation to consumer willingness to share their private information due to privacy concerns. This is the case, especially in the online world (ibid). Related to e-commerce, Van Dyke et al. (2007) found that concerns about privacy have a negative effect on trust.

Based on this previous research, where privacy concerns have shown to negatively influence consumer trust, the following hypothesis is presented:

H9: Higher privacy concerns have a negative influence on trust in AI.

3.9 Research model

Below, a research model is proposed, see Figure 3., to demonstrate the presented hypotheses by showing how each potential predictor affects another variable. The model outlines the constructs that will be measured and visualises a summary of the posed hypotheses.

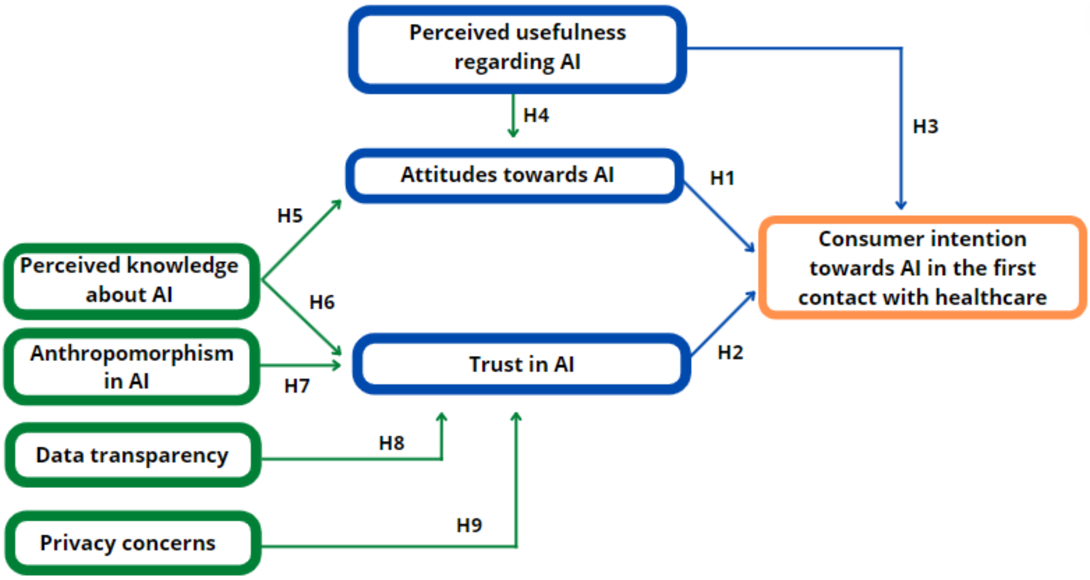

Figure 3: Proposed model with the formed hypotheses.

4. Methodology

Here, the measures, sample as well as processing and interpretation of data will be introduced and discussed. This lays the foundation for understanding how the results will be handled in later chapters.

4.1 Measures

As suggested by Bryman et al. (2017) and Pallant (2016), a pool of scale items was generated from previous literature, see Table 1, to ensure construct validity. This was done to make sure that the items measure the constructs they claim to measure (Hair et al., 2014). Further, the number of questions per construct was ensured to exceed the recommendation of three items to provide sufficient identification for each construct (Hair et al., 2014). The first questions in the questionnaire concern privacy concerns, data transparency, anthropomorphism, perceived knowledge, perceived usefulness, trust, attitudes, and intentions. The last two questions have the purpose of gathering demographic information from the respondents. (See Table 1 for the sources of the survey questions).

After constructing the scales, the same previous literature was used to choose a measure. In the previous studies, the most often utilised measures were the five- and seven-point Likert scales, see Table 1. The Likert scale was used to measure how the respondents feel regarding the questions by rating their feelings on a scale (Jamieson, 2004; Pallant, 2016), in this case, from “Strongly Disagree” to “Strongly Agree”. In the present study, a five-point Likert scale was used to limit the range of different responses.

Table 1: Sources for questions in survey

Litterature	Sector	Sample size	Reliability (Cronbach's α)	Scales	N of items per construct
Bellman et al., 2004	Online privacy	534	0,55–0,95	Likert, 7-point	3-4
Awad & Krishnan, 2006	Online experience	401	0,75	Likert, 3-point	4
Waytz et al., 2010	Technology	32	0,7 – 0,94	Likert, 7-point	5
Edirippulige et al., 2018	E-health	85	0,83	Likert, 5-point	10
Davis, 1989	Information technology	40	0,98	Likert, 7-point	6
Dimitriadis & Kyrezis, 2010	Technology	762	0,89 – 0,91	Likert, 7-point	3-4
Nomura et al., 2008	Robotics and psychology	240	0,65 – 0,78	Likert, 5-point	3-6
Miao et al., 2017	Mobile health	519	0,76 – 0,87	Likert, 5-point	3

The questionnaire was first tested on a small sample (12 individuals) to make sure that the questionnaire was easily understood (Bryman et al., 2017). According to the feedback of the pre-survey, changes were made in terms of wording, adding definitions of core concepts, as well as decreasing the number of the multi-item scales to limit the complexity of the questionnaire.

4.2 Sample

To collect data, the questionnaire was distributed by email to an email list consisting of 4745 students at the faculty of Economics, Business and Law at Gothenburg University. In 2021, 52% females and 48% males were registered at the University (University of Gothenburg, n.d.). Students were chosen as the sample in this study because they are an economically active group, the future consumers of AI in healthcare, plausibly more knowledgeable in AI, and likely to have previous experiences with AI (Ashraf & Merunka, 2017). Additionally, students have been seen to be able to generalise to the whole student population due to their homogenous profile (Ashraf & Merunka, 2017).

The survey was distributed on March 10th, 2022, and was closed for responses after two weeks. Two reminders were sent out, one on March 15th, 2022, and one on March 21st, 2022, to gather more responses as the number of new respondents decreased day by day. To follow the research ethics of information, consent, confidence, and use (Patel & Davidsson, 2019), it was clearly stated that the survey was anonymous with no collection of personal information. The purpose of the survey, as well as its final usage of it, was stated in the introduction of the survey. Lastly, the participation was consented to by the respondents by submitting the finished survey, and it was made clear that they could answer as many questions as they wanted to and exit the survey at any time.

4.3 Processing and interpretation of data

The data was tested for outliers through the stem-and-leaf plots of the data (Hair et al., 2014). There were no responses deleted due to this test as there was no distinguished pattern in the outliers. Furthermore, the missing values were determined to be missing at completely random, according to the little's missing completely at random test, which was statistically insignificant (Hair et al., 2014).

Seven responses were removed due to missing data being over 10%, meaning that the respondents had multiple unanswered questions. The analysis was tested with and without deleted cases to ensure there was no big change in relationships (Hair et al., 2014). After removing respondents with large amounts of missing data, the remaining missing values were substituted with scale-level mean-value substitution. According to Downey and King (1998), mean-value substitution is acceptable, when the amount of missing data is under 20%. The total respondent number was 241 on all scales with the chosen method, thus remaining sufficient (Hair et al., 2014).

Statistical Package for the Social Sciences (SPSS) was used to analyse the data (Carvalho de Mesquita & Kostelijk, 2021). Further, SPSS Amos was used to test the proposed model and run a Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM). In the processing of the collected data, the scale of the variable attitude was recoded (and thus reversed) since the questions were asked negatively. This was done to make the result interpretation simpler.

To assess the reliability of the items, the standardised factor loadings were analysed (Hair et al., 2014). This was done to evaluate if the questions can be grouped together and put in the same category (ibid). After, the Average variance extracted (AVE) and Composite Reliability (CR) were calculated to ensure convergent validity (Hair et al., 2014). As a consequence of too low AVE for five items, anthropomorphism 3, trust 1, attitudes 1, attitudes 2, and perceived usefulness 3, see Table 3, were removed. By removing attitudes 1 and attitudes 2, the number of items for attitudes are lower than the recommended number of three (Hair et al., 2014) which would indicate a weaker construct validity. However, they were removed to increase the value of AVE and CR, to strengthen the construct validity.

Model fit was checked in CFA to see how well the proposed model reflects on the observed data (Hair et al., 2014). This was analysed through different Goodness of Fit measures (Hair et al., 2014). The model fit was measured with Comparative Fit Index (CFI), Tucker Lewis Index (TLI), Normed chi-square, and a badness-of-fit index The Root Mean Square Error of Approximation (RMSEA) (Hair et al., 2014).

SEM was performed to examine the relationships between the independent variables, the mediating variables, and the dependent variable. Model fit was checked to test if the proposed hypotheses were in line with the previous theory (Hoyle, 2012). The p-value was calculated to conclude if the hypotheses were to be rejected or not (Pallant, 2016). In this study, a significance level of 95% was applied, meaning that the p-value should be below the predetermined level of 0,05 to not be rejected (Gray & Kinnear, 2012).

5. Results

In this chapter, the results from the survey will be compiled and presented. The results from the reliability test, the correlation analysis, CFA, and SEM will be presented and explained.

5.1 Descriptive statistics

The response rate from the survey was 5,2% (248 students). Willott (2019) highlights that a 5% response rate is considered typical in an email survey from an unknown sender. Additionally, to be able to perform a factor analysis, a minimum sample of 50 observations and ideally more than 100 is required (Hair et al., 2014), thus making the 5,2 % (248 respondents) acceptable.

241 responses were kept after the data cleaning where 49,8% of the respondents were males and 47,3% were female, (as well as 2,5% preferring not to disclose their gender and 0,4 % missing responses) see Table 2, indicating a representative sample of the students at the School of Economics, Business and Law where the distribution of the students are 48% male and 52% female (University of Gothenburg, n.d.). The years of study showed an even distribution among the students' completed years of their studies, see Table 2.

Table 2: Demographic data

Gender	Percentage	Frequency
Male	49,8	120
Female	47,3	114
Prefer not to say	2,5	6
Missing	0,4	1
Total	100	241
Years of study		
Less than 1 year	9,1	22
1 year	9,5	23
2 years	12,0	29
3 years	19,1	46
4 years	14,5	35
5 years	15,4	37
More than 5 years	19,5	47
Missing	0,8	2
Total	100	241

A table of all questions with corresponding results were compiled to get an overview of the respondents' answers, see Table 3. Studying the results of privacy concerns, 41,9% agreed and 19,5% strongly agreed that it bothers them when asked to provide personal information online, 44% agreed and 27% strongly agreed that they usually think twice before providing their personal information online and 33,6% agreed and 29% strongly agreed that they are concerned that too much of their personal information is being collected online. Lastly, 36,1% agreed and 36,1% strongly agreed that they are concerned about their personal information being used for purposes that they are not aware of.

Looking at the results of data transparency, 47,7% agreed and 30,3% strongly agreed that they believe it is important to them to know why their information is being collected, 40,7% agreed and 26,1% strongly agreed that it is important for them to know if the information collected identifies them, 44% agreed and 27,8% strongly agreed that it is important for them to know what information is being kept about them in a database and 36,1% agreed and 15,4% strongly agreed that it is important to them to know how long their information will be kept in a database, see Table 3.

The results regarding anthropomorphism show that the majority of the respondents felt neutral. 36,5% were neutral about feeling encouraged to interact with AI if it had a human appearance, 40,2% were neutral about feeling encouraged to interact with AI if it was capable of making its own decisions, 35,7% were neutral about feeling encouraged to interact with AI if it had values and norms, and 31,5% were neutral about feeling encouraged to interact with AI if it had emotions of its own, see Table 3.

Studying the results of perceived knowledge, 51% of the respondents agreed and 17,8% strongly agreed that they are familiar with the concept of AI, 34,9% agreed and 8,3% strongly agreed that they feel confident regarding their general knowledge about AI and 32,8% agreed and 11,6% strongly agreed that they feel confident describing AI to a friend, see Table 3. However, the respondents had mixed feelings regarding their knowledge about AI in services and the majority (36,1%) felt neutral about the statement.

The results regarding perceived usefulness show that 42,7% of the respondents agreed and 4,1% strongly agreed that they find AI to be useful for them, 46,9% agreed and 10,8% strongly agreed that AI would make using services easier and 46,9% agreed and 14,9% strongly agreed that AI would enable them as a customer to get serviced more quickly, see Table 3. On the other hand, the majority (47,3%) of the respondents felt neutral that AI would be more convenient for them.

Studying the results of trust, the majority of the respondents felt neutral. 43,6% of the respondents were neutral regarding AI being safe for them when using it, 41,1% felt neutral regarding AI being trustworthy when using it, 45,6% were neutral regarding AI providing them with the desired service level and 45,2% were neutral regarding AI operating as expected to what has been promised, see Table 3. Even though the majority is neutral regarding these statements, more respondents agree than disagree.

The results regarding attitudes imply that the respondents had mixed feelings regarding the statements, see Table 3. The answers are evenly distributed between disagree, neutral and agree regarding that they feel that if they depend on AI too much, something bad might happen and that they dislike the idea of AI making judgements. 41,1% of the respondents disagreed and 9,1% strongly disagreed that they would feel uneasy if AI was used in services and 32,4% disagreed and 12,4% strongly disagreed that they would feel uncomfortable communicating with an AI device.

Lastly, the results regarding intentions show that the respondents, again, had mixed feelings regarding statements, see Table 3. The answers are evenly distributed on disagree, neutral and agree that they plan to receive help from an AI device for their first appointment, would like to get help from an AI device for their first appointment and have intentions to get help from an AI device for their first appointment. However, 39,8% agreed and 10,8% strongly agreed that they will probably use this service in the future.

Table 3: All questions asked in the survey with corresponding results in %. 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree & 5 = strongly agree

Privacy concerns	1	2	3	4	5
1. It bothers me when I'm asked to provide my personal information online.	4,6	12,4	21,6	41,9	19,5
2. I usually think twice before providing my personal information online.	2,9	9,5	16,6	44,0	27,0
3. I am concerned that too much of my personal information is being collected online.	2,9	16,6	17,8	33,6	29,0
4. I am concerned about my personal information being used for purposes that I am not aware of.	3,3	9,5	14,9	36,1	36,1
Data transparency					
1. I believe it is important to me to know why my information is being collected.	2,9	7,5	11,6	47,7	30,3
2. It is important to me to know if the information collected identifies me.	4,6	10,4	18,3	40,7	26,1
3. It is important to me to know what information is being kept about me in a database.	2,1	10,4	15,8	44,0	27,8
4. It is important to me to know how long my information will be kept in a database.	6,6	14,9	27,0	36,1	15,4
Anthropomorphism					
1. I would feel encouraged to interact with AI if it had a human appearance.	19,9	25,3	36,5	14,9	3,3
2. I would feel encouraged to interact with AI if it was capable of making its own decisions.	10,8	20,7	40,2	24,1	4,1
3. I would feel encouraged to interact with AI if it had values and norms.	12,0	16,2	35,7	29,5	6,6
4. I would feel encouraged to interact with AI if it had emotions of its own.	26,3	22,4	31,5	16,2	3,3
Perceived knowledge					
1. Generally, I am familiar with the concept of AI.	2,1	7,5	21,6	51,0	17,8
2. I feel confident regarding my knowledge about AI in services.	5,4	27,4	36,1	23,7	7,5
3. I feel confident regarding my general knowledge about AI.	5,0	22,8	29,0	34,9	8,3
4. I feel confident describing AI to a friend.	8,3	18,7	28,6	32,8	11,6
Perceived usefulness					
1. Generally, I find AI to be useful for me.	4,6	12,0	36,5	42,7	4,1
2. Using AI would make using services easier.	3,7	9,1	29,5	46,9	10,8
3. Using AI would enable me as a consumer to get serviced more quickly.	1,7	9,1	27,4	46,9	14,9
4. Using AI would be more convenient for me.	7,1	17,0	47,3	24,1	4,6
Trust					
1. I believe that using AI is safe for me when I am using it.	3,3	13,7	43,6	34,0	5,4
2. Generally, I believe that using AI is trustworthy.	5,0	17,4	41,1	30,3	6,2
3. I believe that AI will provide me with the desired service level.	4,6	13,3	45,6	34,0	2,5
4. I believe that AI operates as expected to what has been promised.	4,6	19,1	45,2	25,3	5,8
Attitudes					
1. I feel that if I depend on AI too much, something bad might happen.	9,5	22,8	27,8	28,6	11,2
2. I dislike the idea of AI making judgements.	5,8	23,2	32,4	25,3	13,3
3. I would feel uneasy if AI was used in services.	9,1	41,1	32,8	11,6	5,4
4. I would feel uncomfortable communicating with an AI device.	12,4	32,4	30,7	19,1	5,4
Intentions					
1. I plan to receive help from an AI device for my first appointment.	16,2	25,3	34,4	19,9	4,1
2. I would like to get help from an AI device for my first appointment.	13,7	25,3	31,1	23,7	6,2
3. I would choose to get help from an AI device for my first appointment.	15,8	25,3	29,5	22,4	7,1
4. I will probably use this service in the future.	6,6	13,7	29,0	39,8	10,8

5.2 Confirmatory Factor Analysis

All standardised factor loadings were above the limit of 0,5 as well as all the AVE except for trust and attitudes, see Table 4 (Hair et al., 2014). However, according to Fornell and Larcker (1981), AVE less than 0,5 is adequate if CR is higher than 0,6. Furthermore, all CR were above the limit of 0,7 except for attitudes, see Table 4, (ibid), indicating convergent validity, meaning that all items within each variable measured the same thing. The correlations from Table 5 were squared and compared with the AVE, making sure that the square of the correlation between each independent and the dependent variable was lower than the two variables AVE (Hair et al., 2014). This indicates that the constructs show discriminant validity, meaning that the constructs measure different things.

Table 4: Standardised factor loadings, AVE and CR

Variables	Items	Standardised factor loading	AVE	CR
Privacy concerns	1	0,669	0,503	0,799
	2	0,573		
	3	0,822		
	4	0,749		
Data transparency	1	0,707	0,591	0,852
	2	0,749		
	3	0,851		
	4	0,761		
Anthropomorphism	1	0,719	0,509	0,756
	2	0,648		
	4	0,768		
Perceived Knowledge	1	0,776	0,632	0,873
	2	0,772		
	3	0,856		
	4	0,772		
Perceived usefulness	1	0,784	0,527	0,768
	2	0,631		
	4	0,753		
Trust	2	0,741	0,462	0,720
	3	0,684		
	4	0,609		
Attitudes	3	0,727	0,499	0,665
	4	0,685		
Intentions	1	0,852	0,753	0,924
	2	0,894		
	3	0,921		
	4	0,800		

The correlation results from the CFA are shown in Table 5. Studying intentions as the dependent variable, the results showed that attitudes and intentions have a correlation of 0,572, indicating a positive strong relationship (Pallant, 2016), in line with previous studies. Looking at intentions and trust, the results showed a correlation of 0,609, indicating a positive strong relationship in line with previous studies. Lastly, the relationship between intentions and perceived usefulness showed a correlation of 0,631, also indicating a positive strong relationship in line with previous research.

Studying attitudes as the mediating variable, the results implied that perceived usefulness and attitudes have a correlation of 0,572, indicating a positive strong relationship in line with previous research, see Table 5. The relationship between attitudes and perceived knowledge showed a correlation of 0,306 indicating a positive medium relationship (Pallant, 2016).

When studying trust as the other mediating variable, the results implied that trust and perceived knowledge have a correlation of 0,308 a positive medium relationship, see Table 5. Trust and anthropomorphism have a correlation of 0,655, a positive strong relationship in line with previous studies. Trust and data transparency have a correlation of -0,215, a low negative relationship. Lastly, trust and privacy concerns have a correlation of -0,371, a negative medium relationship.

Studying other relationships in the correlation matrix, other strong relationships could be found, see Table 5. Privacy concerns and data transparency have a correlation of 0,864 indicating a strong positive relationship (Pallant, 2016). Perceived usefulness and trust share a correlation of 0,870, a positive strong relationship. Lastly, trust and attitudes share a correlation of 0,629, a positive strong relationship.

Table 5: Correlation matrix for all variables at a 0,05 significance level

	Privacy concerns	Data transparency	Anthropomorphism	Perceived knowledge	Perceived usefulness	Trust	Attitudes	Intentions
Privacy concerns	1,000							
Data transparency	0,864	1,000						
Anthropomorphism	-0,209	-0,100	1,000					
Perceived knowledge	-0,057	0,033	0,166	1,000				
Perceived usefulness	-0,105	-0,006	0,554	0,314	1,000			
Trust	-0,371	-0,215	0,655	0,308	0,870	1,000		
Attitudes	-0,395	-0,362	0,276	0,306	0,572	0,629	1,000	
Intentions	-0,179	-0,107	0,324	0,140	0,631	0,609	0,572	1,000

In the CFA the normed chi-square was 1,595, see Table 6, which is within the threshold of 1-5 (Hair et al., 2014). The CFI was 0,946, see Table 6, which is above the minimum good value of 0,9 (ibid). The TLI was 0,935, see Table 6, which is close to the desired level of 1 (Hair et al., 2014). The RMSEA was 0,050, see Table 6, which indicates a good fit as it is below the maximum of 0,09 (Hair et al., 2014). The above measurements were within the desired thresholds, and under and above desired limits indicating a good model fit.

Table 6: CFA for the constructed model

Chi-square	1,595
CFI	0,946
TLI	0,935
RMSEA	0,050

5.3 Structural Equation Modelling

Table 7 shows the p-value for all proposed relationships at a 0,05 significance level. The results from the SEM indicated that all relationships were significant except for privacy concerns and data transparency where the p-values were above 0,05, see Table 7. This further means that H1, H2, H3, H4, H5, H6, and H7 are not rejected, while H8 and H9 are rejected.

Table 7: P-value for all proposed relationships at a 0,05 significance level

Hypotheses	P-value	Support
H1: Positive attitudes toward AI have a positive effect on consumer intention toward AI in the first contact with healthcare.	0,004	Yes
H2: Higher trust in AI has a positive effect on consumer intention toward AI in the first contact with healthcare.	0,001	Yes
H3: Higher perceived usefulness regarding AI has a positive effect on consumer intentions toward AI in the first contact with healthcare.	***	Yes
H4: Higher perceived usefulness regarding AI has a positive effect on attitudes toward AI.	***	Yes
H5: Higher perceived knowledge regarding AI has a significant positive effect on attitudes towards AI.	0,027	Yes
H6: Higher perceived knowledge regarding AI has a positive influence on trust in AI.	0,003	Yes
H7: Anthropomorphism in AI positively influences trust in AI.	***	Yes
H8: Higher degree of data transparency has a positive influence on trust in AI.	0,913	No
H9: Higher privacy concerns have a negative influence on trust in AI.	0,308	No

Figure 4 visualises the effects that the independent variables had on the dependent and the mediating variables, as well as the effects that the mediating variables had on the dependent variable. The results showed that attitude has a positive effect of 0,280 on intentions, trust has a positive effect of 0,211 on intentions and perceived usefulness has a positive effect of 0,376 on intentions, see Figure 4. Further, perceived usefulness has a positive effect of 0,533 on attitudes, and perceived knowledge has a positive effect of 0,173 on attitudes. Lastly, perceived knowledge has a positive effect of 0,210 on trust, anthropomorphism has a positive effect of 0,568 on trust, data transparency has a negative effect of -0,023 on trust (not supported), and privacy concerns have a negative effect of -0,226 on trust (not supported).

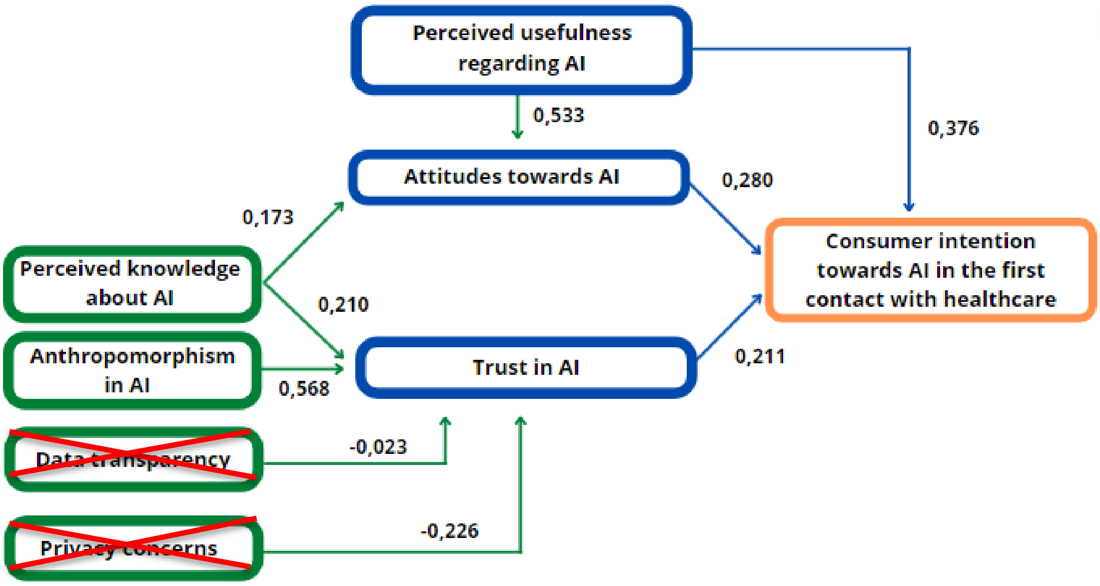

Figure 4: Proposed model with estimates from SEM

Table 8 shows the measurements for SEM where the normed chi-square was 2,116, see Table 8, within the threshold of 1-5 (Hair et al., 2014). The CFI level of 0,893 was below the desired 0,9, The TLI value was 0,879, close to 1, and RMSEA was 0,068, below 0,09, see Table 8. The results from the SEM indicated a good model fit.

Table 8: SEM for the constructed model

Chi-square	2,116
CFI	0,893
TLI	0,879
RMSEA	0,068

6. Discussion

This research aimed to investigate potential predictors for consumer intentions by investigating multiple relationships between a number of independent variables, mediating variables, and the dependent variable, consumer intention towards AI in the first contact with healthcare. This was done to examine if these independent variables and mediating variables can be used as predictors for consumers' intention toward AI in the first contact with healthcare. Implementing future changes in healthcare with AI could possibly be made easier using the proposed model from the present thesis.

H1 hypothesised that positive attitudes would have a positive effect on intentions, which proved to be significant and therefore not rejected. Meaning that consumers with a more positive attitude toward AI should have higher consumer intention toward AI in the first contact with healthcare. This was in line with previous theories on consumer behaviour (Ajzen, 1991) as well as previous findings on AI and acceptance (Zhu & Sun, 2021). Additional research further found that ambivalent attitudes are common in the context of valuable technology, such as AI (Gessl et al., 2019; Destephe et al., 2015; Lennox-Chhugani et al., 2021), which is in line with the results of the present study, where the respondents had mixed feelings regarding the questions. Further, the correlation between attitudes and intentions was proven to be high and attitudes were proven to be the second strongest predictor for intentions when comparing the three variables tested directly on the dependent variable. It is therefore vital, in the healthcare industry, to positively influence consumer attitudes towards AI when further introducing AI in the industry, following that positive attitude have a positive impact on consumer intentions.

The research further provided support for H2, higher trust has a positive effect on intentions, meaning that the hypothesis was not rejected. In other words, consumers with higher trust towards AI should have higher consumer intention towards AI in the first contact with healthcare. This was also in agreement with previous findings concerning trust and intentions in the context of technology and AI (Asan et al., 2020; Zhu & Sun, 2021; Liu & Tao, 2022; Gefen et al. 2003; Lee & See, 2004; McKnight et al., 2002; Zhang et al., 2019). The results from the survey mostly indicated that the respondents were neutral regarding their trust in AI, but more people agreed that they trust it than disagree. Previous research further highlights that people will not accept AI if they cannot trust the technology (Zhu & Sun, 2021), especially in the context of healthcare where there may be a matter of life and death (Asan et al., 2020). Trust proved to have a strong relationship with intentions, on the other hand, trust indicated having the third strongest effect on intentions when comparing the three variables tested directly on intentions. From this, it is of importance to understand what influences higher consumer trust since it has a positive impact on intentions and could be crucial for the future implementation of AI in healthcare.

H3, higher perceived usefulness would positively affect intentions, and H4, higher perceived usefulness would have a positive effect on attitudes, were proved to be significant and therefore not rejected. Meaning that consumers with higher perceived usefulness regarding AI should have higher consumer intentions toward AI in the first contact with healthcare and a more positive attitude towards AI. This was in line with the Technology Acceptance Model as well as previous research regarding perceived usefulness and intentions in the context of information technology (Davis, 1989; Lee & Wan, 2010) and healthcare (Lennox-Chhugani et al., 2021; Esmaeilzadeh, 2020). It is further in line with previous findings concerning perceived usefulness and attitudes in the context of sales technology usage (Upadhyay et al., 2018) and healthcare (Scott et al., 2021; Lennox-Chhugani et al., 2021). The majority of the respondents from the survey agree that they find AI to be useful for them which is, according to previous research, decisive for consumer intention and attitudes (Davis, 1989; Lee & Wan, 2010; Lennox-Chhugani et al., 2021; Esmaeilzadeh, 2020; Upadhyay et al., 2018; Scott et al., 2021). Additionally, perceived usefulness proved to have a strong relationship with both intentions and attitudes as well as being the strongest predictor of the tested relationships, for intentions and attitudes. This makes perceived usefulness to be the most important variable in predicting consumer intentions and attitudes in this model and present study. If a consumer does not see use in the technology, they would most likely not plan to use it, which would lead to hindrance in the implementation of AI in healthcare.

H5, that higher perceived knowledge would positively affect attitudes, and H6, that higher perceived knowledge would have a positive effect on intentions, were shown to be supported and therefore not rejected. In other words, consumers with higher perceived knowledge regarding AI should have a more positive attitude towards AI and higher trust in AI. In line with previous findings, attitudes and trust were shown to be two mediating variables for knowledge and intention, in the context of technology (Gatignon & Robertson, 1985; Moreau et al., 2001). Additionally, the accepted hypotheses align with previous findings regarding knowledge and attitudes concerning autonomous vehicles (Smith, 2018) and AI (Persson et al., 2021). As well as previous research regarding knowledge and trust in the context of AI (Gillespie et al., 2021). The result from the survey showed that the majority of the respondents feel like they are familiar with the concept of AI. This would then indicate that most respondents could give a more certain response to the AI-related questions, in comparison to an individual to whom the term AI is completely new. Perceived knowledge showed to have a positive medium relationship with both attitudes and trust as well as being the second strongest predictor for attitudes when compared to the two tested variables affecting attitude and the second strongest significant variable when compared to the four tested variables on trust. Therefore, in line with Keller (1993; 2003), it is seen that higher perceived knowledge is a predictor for consumers to act favourably toward AI, due to the positive effect on trust and attitude. Individuals may further feel more confident and positive about AI if they have knowledge of the technology used as they can rationalise the use of the technology.

Moving on to H7, that anthropomorphism had a positive relationship with trust, was further significant and accepted. This means that if AI appeared more human-like, consumer trust in AI would increase. According to the results, anthropomorphism should increase consumers' level of trust in AI. Previous findings have shown that consumers are more inclined to use AI healthcare services if the AI component is human-like, due to a higher level of trust in AI (Troshani et al., 2021; Wickramasinghe et al., 2016; Ruijten et al., 2018). The results from the survey showed that the majority of the respondents were neutral regarding their preferences on AI having a human-like appearance. This may point to respondents either not knowing the meaning of humanlike AI or that they do not grasp the concept of what it would mean to them in a future scenario. Further, anthropomorphism proved to have a strong relationship with trust, as well as being the strongest predictor to trust. Thus, implementing a feature/look could be beneficial for future use of AI in healthcare.

In contrast to all other hypotheses, H8, that a higher degree of data transparency would have a positive effect on trust was not significant and therefore rejected. This means that being more transparent about what consumers' personal information is used for would have a positive influence on consumer trust in AI. Also, not in line with previous research where it has been found that data transparency increases trust (Morey et al., 2015; Nati, 2018), as well as little transparency, leads to less trust (Raz et al., 2020). Again, the data evidence gained in this study was not strong enough to imply an existing relationship between data transparency and trust. Contrary, the results from the survey showed that the majority of the respondents agree that it is important to know why and for how long their personal information is being collected. Again, most of the respondents felt neutral or that they agreed regarding trusting AI. This may be a result of respondents feeling that AI is transparent. Further, the questions asked in the survey concern the importance of data transparency in a general context while the proposed hypothesis states that higher data transparency has a positive influence on trust in AI. Following that the survey does not focus on how the respondents feel regarding data transparency in AI, this hypothesis is not in line with the survey. Hence, the hypothesis is rejected. This is also something that would need to be revised by the present authors and possibly improved in future studies on the subject. An increased number of consumers want to know how their personal information is being handled (Felzmann et al., 2019). An individual's personal information is private and should be handled respectfully (Xiao et al., 2016) to prevent individuals from being worried about what their personal information is used for (Morey et al., 2015).

Lastly, H9, that higher privacy concerns would have a negative influence on trust, was not supported and therefore rejected. In other words, consumers that are more concerned about their privacy would have lower trust in AI. This is not in line with previous findings where it has been shown that privacy concerns and trust are connected in the context of healthcare and new technologies (Dhagarra et al., 2020), as well as the misusing of consumers' personal information, can cause mistrust of a company (Ayaburi & Treku, 2020). The data set and evidence received in this present study were not strong enough to imply that there exists a relationship between privacy concerns and trust in this case. On the other hand, the majority of the respondents agreed that they are concerned about their personal information is online. Further, most of the respondents felt neutral regarding their trust in AI, yet more respondents agreed that they trust AI than disagreed. The questions asked in the survey concern the respondent's degree of general concern regarding their personal information being used and collected online. A concern may be that the questions were not asked in the context of AI and maybe the reason for the hypothesis being rejected. Due to the fact that AI, especially within healthcare, is a different setting than for example online shopping, posing the questions to address the former context specifically could have yielded other responses. Another reason may be that other factors than privacy concerns are more important concerning consumer trust in AI. Following that AI depends on personal data (Rossi, 2018) it is vital that consumers are willing to share their personal information.

From the above, perceived usefulness regarding AI had the strongest influence on consumer intention towards AI in the first contact with healthcare, followed by attitudes towards AI. Meaning that the most valuable factor to take into account for future marketing efforts toward increasing consumer intention concerning AI in healthcare is the potential consumers' perception that the service is useful to them, as well as creating a positive attitude towards AI. Furthermore, it may be vital to focus on increasing potential consumers' trust in AI which may be done, based on the results from the present study, by making a future AI device more human-like. Lastly, informing potential consumers about a future service like this and how it works may further be of importance in its development.

The sample of respondents who completed the survey was regarded as representative by the present authors due to its similarity of the percentage of female versus male respondents in comparison to the population statistics by the University of Gothenburg, (n.d.) presented earlier. The respondents also were shown to represent all years of study from less than 1 to more than five with a quite even distribution. Even though no population statistics on the year of study could be found for comparison, the data of this demographic helped to show that respondents did not all belong to the same few groups. This would not, however, mean that the sample is fully representative of the population. Other demographic factors (such as age or country of residence) could have been included in the survey questions and compared to existing statistics of the population to further confirm if the sample is representative. For the present thesis, the authors did rely solely on gender since other factors seemed less relevant to the study. This is thus something that could have been done differently, but that was done under consideration while weighing advantages and disadvantages carefully.

It may be of interest to study other strong relationships found in the correlation matrix, such as privacy concerns and data transparency with a correlation of 0,864, perceived usefulness and trust with a correlation of 0,870, trust and attitudes with a correlation of 0,629, and perceived usefulness and anthropomorphism with a correlation of 0,554.

Studying the results from the survey, the respondents were concerned about their personal information being online, as well as knowing what their personal information is being used for in an online context. A strong positive relationship was shown between the variables, meaning that the more concerned the respondents are regarding the personal information being used online the more important it is to them to know what their information is being used for and vice versa.

Next, a strong relationship between perceived usefulness and trust, indicates that the more the respondents feel like AI is useful to them the more they should trust AI. To further reflect, if they see a personally beneficial purpose with the AI service, it would be logical that it could be more trustworthy. Studying the responses from the survey, the majority of the respondents agreed that they perceived AI to be useful to them, while they mostly felt neutral as well as agreed that they feel like they can trust AI. It may be of interest to study this relationship further following that it most likely would increase consumer intention and therefore can be of importance when marketing the healthcare service.

Lastly, the strong relationship between attitudes and trust implies that consumers with a higher positive attitude towards AI should have a higher level of trust in AI conversely. In this case, the answers were mixed regarding attitudes towards AI, and again trust in AI was mostly neutral followed by the respondents agreeing to the statements. This may also be of interest to further investigate since, in this case, the correlation was strong. On the other hand, it is difficult to discuss the relationship by only reviewing the result from the survey due to the mixed and neutral answers.

For future research on this topic, one recommendation is to perform similar research in other countries and settings as well as other groups of individuals to find out how different respondents view the phenomenon of AI in healthcare. Other potential predictors to consumer intention toward AI in the first contact with healthcare can be studied and added to the proposed model in this study. An additional proposal for future research is to conduct the study within different areas of healthcare. Furthermore, a qualitative method approach can be interesting to use, allowing future researchers to gain a deeper understanding of what individuals feel and think regarding this topic. Other responses and reflections may come forward, adding to the present thesis' results. A last suggestion for future studies is to focus on the predictors for perceived usefulness since it had the strongest impact on both consumer intentions and attitudes. Also, studying other strong relationships found in this research, such as the relationship between privacy concerns and data transparency, perceived usefulness and trust, as well as trust and attitudes.

7. Limitations

The results are not generalisable to a larger population than students at GU, School of Business, Economics and Law, since this was the sample that was utilised. This may hinder a wider usage of the model in the future implementation of AI in healthcare. However, with the generalisation aspect and limitation in mind, the authors believe that the constructed model can be used for this purpose, as a guideline. Due to the selection of respondents, it is not certain whether the findings of the present thesis would be true outside of Sweden, which is another point that is kept in mind by the present authors. Moreover, since the scenario in the survey is hypothetical, there are no limitations on the respondents' experience with AI in healthcare. Further, another limitation would be that the present thesis only focused on the intention to use AI for the first contact with healthcare and just regarding light symptoms, thus making it impossible to generalise the results in other healthcare areas. The choice of method (quantitative) could also be considered limiting in not allowing free reflection from respondents by only offering a set number of options in each question in the survey. This opens other angles of the way of studying the same research question, which could be brought up in future research.

8. Conclusion

The present study was conducted to investigate predictors of consumer intention toward AI-based healthcare services, with a focus that AI has the possibility to eliminate or decrease misdiagnosing and enhance efficiency within healthcare. More precisely, to examine predictors of consumer intentions towards AI in the first contact with healthcare and to answer the proposed research question: *What factors influence consumers' intention toward AI within healthcare?*

Attitudes, trust, and perceived usefulness were tested directly to influence consumer intention and these three hypotheses showed to be significant and not rejected. Perceived usefulness was shown to be the strongest predictor in this case. Further, perceived usefulness and perceived knowledge were both tested to affect consumer attitudes where both hypotheses proved to be significant and not rejected. Again, perceived usefulness showed to have the strongest influence. Lastly, perceived knowledge, anthropomorphism, data transparency, and privacy concerns were tested to affect trust. In this case, the hypotheses concerning perceived knowledge and anthropomorphism showed to be significant and not rejected, while the hypotheses concerning data transparency and privacy concern proved to be insignificant and therefore rejected. Here, anthropomorphism showed to have the strongest influence on trust.

With these findings, conclusions can be drawn that stronger consumer intentions toward AI-based healthcare services will most likely be reached by focusing on making potential consumers feel like the service is useful to them, focusing on creating a more positive attitude and making them feel like they can trust the service. With the highest focus on perceived usefulness following that this variable was the strongest predictor of consumer intention. This may further be done by focusing on marketing the service to make potential consumers gain more knowledge about AI in healthcare and make the AI services appear in a more human-like way.

To answer the proposed research question: *What factors influence consumers' intention toward AI within healthcare?* It is presented that attitude towards AI, trust in AI, and perceived usefulness regarding AI directly influence consumers' intention toward AI within healthcare. As well as perceived usefulness regarding AI, perceived knowledge about AI, and anthropomorphism in AI affect consumers' intention toward AI within healthcare through the mediating variables attitudes towards AI and trust in AI.

If AI can be used to eliminate or decrease misdiagnosing and to enhance efficiency within healthcare, it is vital to understand what predicts and enhances consumer intentions toward the service because it is a matter of saving people's lives, improving their well-being and everyday life. The importance of this subject was one of the reasons for the choice of field of study for the present thesis.

The present thesis contributes to the narrow field of study of AI and healthcare from a consumption and consumer perspective. The findings of the present thesis could also assist in the implementation of AI in healthcare as well as the future marketing of AI in healthcare. The model found through this study could show what aspects to focus on and what is important to the consumer. This may in turn aid healthcare in society as a whole, if AI functions to the advantage of healthcare, i.e., that it makes patient care more efficient.

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Appendix - Survey

Introduction to survey:

This survey is a part of a master's thesis written at the University of Gothenburg with a focus on attitudes concerning artificial intelligence within healthcare in the future. This survey will be the base of the study. You will be asked to give your opinion in regards to a number of statements.

The first statements will cover general issues regarding online data collection, followed by statements about your perception of artificial intelligence. After that, a scenario will be presented from which you'll be asked to answer statements in connection to the scenario. Lastly, a few demographic questions will be asked.

Your answers to this survey will be handled anonymously, meaning that no personal information will be shared.

Thank you for contributing to our research.

Scale: 5-point Likert scale

Survey questions:
Privacy concerns (Questions adapted from Bellman et al., 2004)

1. It bothers me when I'm asked to provide my personal information online.
2. I usually think twice before providing personal information online.
3. I am concerned that too much of my personal information is being collected online.
4. I am concerned about my personal information being used for purposes that I am not aware of.

Data transparency (Questions adapted from Awad & Krishnan, 2006)

1. I believe it is important to me to know why my information is being collected.
2. It is important to me to know if the information collected identifies me.
3. It is important to me to know what information is being kept about me in a database.
4. It is important to me to know how long my information will be kept in a database.

Anthropomorphism (Questions adapted from Waytz et al., 2010)

1. I would feel encouraged to interact with AI if it had a human appearance.

2. I would feel encouraged to interact with AI if it was capable of making its own decisions.
3. I would feel encouraged to interact with AI if it had values and norms.
4. I would feel encouraged to interact with AI if it had emotions of its own.

Artificial Intelligence

When mentioning artificial intelligence (AI) in this survey, we refer to intelligent machines with the capability of behaving, interacting, and appearing in a human-like way.

The following statements concern knowledge, anthropomorphism, trust, perceived usefulness, and attitudes with an overall focus on AI.

Perceived Knowledge (Questions adapted from Edirippulige, Samanta & Armfield, 2018)

1. Generally, I am familiar with the concept of AI.
2. I feel confident regarding my knowledge about AI in services.
3. I feel confident regarding my general knowledge about AI.
4. I feel confident describing AI to a friend.

Perceived usefulness (Questions adapted from Davis, 1989)

1. Generally, I find AI to be useful for me.
2. Using AI would make using services easier.
3. Using AI would enable me as a consumer to get serviced more quickly.
4. Using AI would be more convenient for me.

Trust (Questions adapted from Dimitriadis & Kyrezis, 2010)

1. I believe that using AI is safe for me when I am using it.
2. Generally, I believe that using AI is trustworthy.
3. I believe that AI will provide me with the desired service level.
4. I believe that AI operates as expected to what has been promised.

Attitudes (Questions adapted from Nomura, Kanda, Suzuki & Kato, 2008)

1. I feel that if I depend on AI too much, something bad might happen.
2. I dislike the idea of AI making judgements.
3. I would feel uneasy if AI was used in services.
4. I would feel uncomfortable communicating with an AI device.

Scenario:
You are at the doctor’s office for the first appointment with your new doctor. You come in with light symptoms of coughing and a sore throat. When being told to come in for the examination, you find out that your symptoms will be checked by an AI device. Here, an AI

device refers to a future device, for example, a machine, that can evaluate your symptoms, using AI algorithms.

The following statements concern your intention to use AI for the first appointment with your new doctor.

Intentions (Questions adapted from Miao, Wu, Wang, Zhang, Song, Zhang, Sun, Jiang, 2017).

1. I plan to receive help from an AI device for my first appointment.
2. I would like to get help from an AI device for my first appointment.
3. I would choose to get help from an AI device for my first appointment.
4. I will probably use this service in the future.

Demographics:

- Gender:

Male/Female/Would not like to specify

- Years of study

Less than 1, 2, 3, 4, 5, More than 5