Determinants of AI Privacy Perception

How Knowledge and Context Influence People’s Opinion of AI

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ABSTRACT

Artificial Intelligence (AI) is becoming increasingly important for businesses to improve their work, and make it more efficient and user-friendly. Using user data, AI systems can create personalised recommendations in many different contexts, enabling widespread adoption of AI. Numerous determinants can influence people's perception of AI, and it is necessary to find out how and when they influence people's perception to be better able to influence people's perception of AI when needed. This study therefore tries to find out whether knowledge of AI privacy implementations and the context in which an AI system is used affect people's perception of AI. Knowledge about AI privacy implementations can differ amongst people because there are many different experiences and interests people have had, which could potentially influence people's perceptions of AI. Additionally, AI systems are used in many different contexts, such as film recommendations and medical diagnosis, with varying degrees of importance of personal data that is used by the AI systems. The variable context will therefore be studied as a potential moderating variable in the relationship between knowledge of AI privacy implementations and perception of AI. Together, this leads to the question of "to what extent knowledge of privacy implementations in artificial intelligence has an effect on people's perception of artificial intelligence, and whether this differs between the importance of the context".

A 2x2 between-subjects experiment (*N* = 131) was done to answer the research question. The two-way ANOVA test showed no significance for all effects. Knowledge of AI privacy implementations and the context in which the AI systems are used are both not significant determinants of people's perception of AI. However, the moderating relationship was very close to significance and a power analysis revealed low power for the main analysis, so the decision was made to perform supplementary analyses. Here, perception of AI was split into trust in AI and usefulness of AI. These analyses showed that context is a significant determinant of trust in AI, and the moderating relationship between knowledge and context is also significant for trust in AI. Even though the main results were not significant, the mean differences show that less knowledge in a lower-stakes Netflix context leads to the most positive perception of AI, whereas little knowledge in a higher-stakes medical context works the opposite and creates the most negatively perceived perception of AI. This study therefore provides relevant, new and insightful information on the determinants of perception of AI and can help businesses that are working with AI.

KEYWORDS: *Artificial Intelligence, Privacy, User Perceptions, Knowledge, Context*

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1. Introduction

Artificially Intelligent (AI) decision-making processes are improving and are slowly starting to get more involved in our everyday lives. They are used worldwide in many different industries, such as relatively low-stakes entertainment contexts to make movie and music recommendations, and high-stakes environments to make decisions about people's allowances or job applications (Rai, 2020, p.137). AI models can be used for many different purposes, such as text, image, audio and video generation and each of these is used by various businesses in different contexts across the world (Dreibelbis, 2023). AI models can be very beneficial but also need to be improved continuously. One of the ways they do this is by looking at user data (OpenAI, 2023). This can lead to privacy concerns because there are a lot of uncertainties regarding how personal data is collected and where it is used (Tucker, 2019, p.423). Even big companies cannot always guarantee complete safety. In 2023, Microsoft AI researchers accidentally exposed 38TB of data (Ben-Sasson & Greenberg, 2023). This is problematic because all of a sudden people's private information was openly available to the wider public, which causes big risks for identity theft, fraud and scams. When these large companies are already not able to keep adequate privacy protection, what can people expect of other entities dealing with their data? It leads to even more privacy concerns for users. Because AI is becoming very important in so many different aspects of life and comes with ongoing privacy risks, it is important to find out how people perceive the way that AI deals with their privacy and if knowledge of the AI privacy implementation and the use of AI models in different contexts affect this.

AI is constructed in a way which requires a lot of data to learn. This data is often based on personal information (Sher & Benchlouch, 2023). As AI is becoming more popular, users need to know exactly what they are getting into and what the consequences are for their privacy when they use the models. New laws and regulations such as the European AI Act try "to ensure better conditions for the development and use of this innovative technology" (European Parliament, 2023). However, there are many cases in which researchers have found mistakes in AI models. Recently, ChatGPT released over 30 email addresses from New York Times employees from its training data with easy adjustments and prompts that bypassed the regular regulations (White, 2023). In another case, researchers from the University of California found a way to bypass the restrictions and retrieve information from the training data in ChatGPT (Ray, 2023). These are only a few examples of privacy risks that users come across. When this continues to happen, users need to be able to make well-informed decisions about whether they want to use the AI model. This requires knowledge of how they work and what kind of personal information they use.

A less recent, but more striking example is the Dutch childcare benefit scandal, where the Dutch government used algorithms for their risk classification model. The algorithms incorrectly misjudged childcare benefit applications because people with certain backgrounds were more easily marked as fraud (Amnesty International, 2021). This led to distrust in the Dutch government and the algorithms used by them. Many people became victims, which has had major implications for them, as well as for the Dutch government who had to resign (Erdbrink, 2021). It also served as a warning for other governments using algorithms to not let it happen to them as well (Heikkilä, 2022).

As became evident from the previous examples, people can have many different experiences with AI decision-making processes, leading to varying perceptions of it. This study will focus on getting a better understanding of the determinants, specifically whether knowledge of AI privacy implementations and the context in which an AI system is used have an impact on people's perceptions of AI. Knowledge about AI privacy implementations focuses on how much people know about which personal information the AI systems use to provide them with their personal recommendations. This can be different per person, but also per context. Therefore, this is chosen as a second determinant that this study will focus on. Specifically, how the perception of AI changes in a context where AI systems work with lower-stakes personal information versus in a context where they work with higher-stakes personal information. All of these concepts combined lead to the following research question which will be studied in this thesis: *To what extent does knowledge of privacy implementations in artificial intelligence have an effect on people's perception of artificial intelligence, and does this differ between the importance of the context?*

Scientific and Societal Relevance

On a scientific level, not a lot of research has been done on this topic yet. Chatbots equipped with artificial intelligence tools have been studied in relation to privacy concerns, but not to general perception (De Cosmo et al., 2021, p.83). In the social science approach of this thesis, the focus will be on how people perceive AI. Numerous studies have been done on perception, but the specific focus on perception of AI is rare. Any studies that do mention it have other focus points such as perception of AI and its rights or the direct relation to the risks and opportunities (Lima et al., 2020, p.1; Schwesig et al., 2023, p.1053). The combination of these concepts is fairly new, specifically the research focus on determinants of perception of AI and how these can affect how perception is shaped. Previous research has only focused on the determinants of AI literacy (Celik, 2023, p.1). Particularly little research has been done on the effect of knowledge about AI privacy implementations and the context in which AI systems are used as determinants of perception of AI and the combined effect of these variables. AI comes in different shapes and forms and because of this, it is hard to capture the general perception of it. Current literature focuses mainly on algorithms, and any link to perception brings us to theories of algorithm awareness, algorithm aversion and algorithm appreciation (Araujo et al., 2020, p.613; Hou & Jung, 2021, p.1). The current study will therefore focus on enhancing this part of the literature by combining these aspects and trying to gather a better understanding of the role of knowledge and context in the shaping of perception of AI.

The general perception of AI differs greatly amongst the general population and can have many different determinants as has been established before. It is important to know how people's opinion is influenced because in certain cases it can be useful to change this. In the medical context, AI systems can detect certain diseases with 98% accuracy (Kumar et al. 2022, p.8478). Because of the speed with which these systems work, diseases can be detected much quicker by AI systems than by doctors. People can then be diagnosed faster and treated faster as well, which helps to save people's lives. It is therefore important that people view AI positively because they could benefit greatly from it. For this result, it is however first important to figure out what determines people's perception of AI. Next to this, because new regulations such as the Digital Services Act force businesses to be more open about their use of AI systems, people have had the chance to get to know more about AI in recent years (The Digital Services Act (DSA), n.d.). Knowledge still changes a lot, however, and it is unclear how much it affects people's perceptions. To find out whether the new regulations work and help to improve people's perception of AI systems, it is important that this combination is studied. Furthermore, AI systems are now used by businesses in many different contexts (Q.ai, 2023). AI systems in each context use different kinds of information to make their recommendations. It is important to find out how perception changes across contexts and which factors work to determine perception of AI across different contexts. If it is wrongly assumed that perception of AI is influenced by similar factors across low-stakes and high-stakes contexts, the necessary measures that need to be taken might not work as intended. This might then cause that the implementation of AI in situations where it is needed cannot happen because people's perception is influenced by the wrong determinants. In certain high-stakes contexts such as medical diagnosis, the use of AI systems could potentially save lives but if it is not implemented because people's perception is low as a result of the wrong focus on determinants, this could have serious potential effects. Thus, it is very important to study the effect of potential determinants on perception of AI across various contexts with differing amounts of importance.

Chapter Outline

This chapter introduced the topic of the study and its relevance, as well as the research question. The next chapter will provide an overview of the relevant theories regarding perceptions of AI and the determinants that could influence it, with a specific focus on knowledge of AI privacy implementations and the context in which AI systems are used. Chapter three gives a short overview of the methodological decisions of the study and explains the steps which were taken to improve the experiment and survey. It also explains the preparatory steps that were taken before the main analyses could be done. The fourth chapter shows the results of the tested hypotheses and supplementary testing. In the final two chapters, these results are discussed and a conclusion is provided with an answer to the research question. Additionally, this section also provides an overview of the practical and theoretical implications, limitations and strengths of this study and suggestions for future research based on this.

2. Theoretical Framework

Transparency about the functioning of AI systems and their use of personal data is needed for people to get a better understanding and make more informed decisions on whether and how they want to use the system. Public knowledge of AI differs a lot, leading to different expectations and opinions (Nader et al., 2022, p.11). The focus of this study is therefore on the relationship between the amount of knowledge someone has of AI privacy implementations and their perception of AI. Because AI is used in so many different contexts, it can be hard to keep up with how it works and what it is used for. In most cases it works well, but just like humans, AI systems can make mistakes. Especially in crucial contexts where personal information is used by AI systems, it is important that they can be trusted. The variables knowledge of AI privacy implementations and perception of AI have not often been studied together before, but based on other theories such as algorithmic appreciation and algorithmic aversion, hypotheses can be made up. Since the context in which an AI system operates matters a great deal for what kind of personal data it uses, which in turn can lead to different perceptions because people perceive some data to be more important than others, this will also be included in the current study as a moderating variable. Theories such as privacy fatigue and privacy calculus will be used in this case to make predictions. Even though the combination of these three variables in a study is fairly new and has not been studied in this way before, related theories and research will be used to create predicting hypotheses.

The Connection Between Knowledge of AI Privacy Implementations and Perception of AI

AI systems are built in a certain way that makes the program work, but they need data and information to improve and be continuously updated. This data comes from many different people in different contexts, leading to privacy concerns because it is often ambiguous how the data is stored and used. There are three main types of concerns regarding data collection and data usage by AI systems. The first concern is data persistence, where data may potentially exist and be used for longer than the person who created it. The second concern is data repurposing, which is about data being repurposed for a different purpose than for which it was originally collected. The last concern is about data spillovers, which concerns data reaching people who were not intended to see it (Tucker, 2019, p.423). Thus, some of the main concerns are about the data being stored, traded and used long after it is collected, as well as data breaches where the data reaches people who were not intended to see it (Jin, 2019, p.442-443; Khosravy et al., 2022, p.931). Developments in recent years have improved the systems, with new rules and regulations bringing more focus on privacy issues. However, there are still many privacy and security violations, as the system is not completely foolproof yet. One of the most recent examples of these violations is that ChatGPT provided strangers with e-mail addresses even though it should not have been able to do so (White, 2023). ChatGPT is not allowed to share personal information with strangers, but the e-mail addresses from New York Times employees passed through the cracks of the system and were able to be shared even with the strong rules. A study by Kronemann et al. (2023, p.11) found that privacy concerns about consumer data through AI negatively affect consumers' evaluations of digital assistants. When a user has privacy concerns regarding their personal data, they do not want to share their personal information or simply refuse to use a certain technology. The privacy concerns negatively affect people's attitude and their willingness to share personal information. This means that if privacy concerns about AI are higher, perceptions of AI will be more negative. Strong regulations can be put into place, but if they do not work and privacy concerns become stronger, perceptions of AI will only become worse.

This reluctance towards AI systems is also called algorithm aversion, which is the phenomenon where people prefer human forecasters over algorithms (Dietvorst et al., 2015, p.114). People are especially averse towards the decisions made by algorithmic forecasters, even when they are better than the ones made by human forecasters. Algorithmic forecasters are not perfect, and can also make mistakes. These mistakes, however, are far less accepted than mistakes made by human forecasters and much stronger accounted for, lowering preference for the algorithmic forecaster even more (Dietvorst et al., 2015, p.125). Reich and colleagues (2023, p.298) demonstrated that perceived learning from mistakes mediates this effect. People often believe that humans are more capable of learning from their mistakes than algorithms, and thus put more trust in them instead of in algorithmic forecasters. However, when presented with the evidence that algorithms can learn from their mistakes and improve themselves, trust in both forecasters was perceived equally. Thus, more knowledge about an algorithm results in better trust and more reliance on the algorithmic forecaster's predictions, although this still only results in the same level of trust as in human forecasters and nothing beyond it. If one tries hard to improve trust in algorithmic forecasters by presenting people with more information about how well the algorithm works, the best they can get is the same level as trust for human forecasters and it is very hard to get more than this (Reich et al., 2023, p.298).

Contrary to algorithm aversion is algorithm appreciation, which is a phenomenon which shows that people are more likely to follow advice from algorithms than from humans (Logg et al., 2019, p.90). Participants from the study by Logg and colleagues (2019, p.99) relied more on algorithmic advice, especially for certain tasks such as making visual estimates or predicting the popularity of songs or romantic attraction. Algorithmic appreciation only applies to a certain extent, however, because expert forecasters were less keen to take advice from algorithms, causing them to get more negative results than if they had trusted the algorithm. More experience with algorithms does therefore not always automatically lead to more appreciation of the algorithm. Further research shows that algorithmic appreciation decreases when transparency about the algorithm's prediction errors increases (You et al., 2022, p.358). When algorithmic appreciation occurs, trust is usually higher in an algorithm than in a human predictor. However, when more detailed information is provided on how the algorithm works and how often it makes mistakes, algorithm appreciation decreases and advice from algorithms is not trusted to the same extent anymore.

Algorithm appreciation and algorithm aversion are found to have a common factor that influences them, namely expert power (Hou & Jung, 2021, p.20). Whether people will show algorithm appreciation or algorithm aversion is related to how the algorithm is framed compared to the human. The main reason for how people react is all about framing, how a certain algorithm is framed and how the human forecaster is framed. Next, how much power they have in relation to each other is also a key aspect of how people will react. When a human is presented to be better at making decisions than an algorithm, people will show more signs of algorithm aversion because they feel like they can put less trust in the algorithm and the decisions it makes. However, when an algorithm is presented to work just as well as a human, or even better, it will often lead to algorithm appreciation. The key to the extent that people trust algorithms is all about how they are framed in relation to the human decision-maker. Even though the perceptions of algorithms can be explained like this for most cases, there can still be outliers from people who rely on different points to form their opinion of the algorithm such as the expert forecasters from the article by Logg and colleagues (2019). Next to this, a stronger focus on the learning abilities of the algorithm or more focus on the algorithmic errors can also influence people's perception, as it is also a way to frame the way they see it. When dealing with sensitive personal information, algorithmic errors can have a severe impact on someone's privacy. Consequently, algorithmic appreciation and algorithmic aversion are important predictors of people's AI perception.

Perceptions of AI, and specifically algorithms, can therefore vary a lot. This also applies to recommender systems, one of the most well-known types of artificial intelligence algorithms. These algorithms use input such as personal information to create an output, which gives a certain recommendation, for example, song or playlist recommendations on Spotify and video recommendations on YouTube (Yedidi, 2023). However, in most cases, it is not clear to users how the recommender systems work and how the technology behind them uses people's information. Consequently, a need for algorithmic transparency arises that will explain how it works. If people do not know how the algorithm operates, they cannot make informed decisions on their opinions. A study by Shin and colleagues (2022, p.9-10) has shown that algorithmic awareness influences people's trust in algorithmic processes and the way that users evaluate the privacy concerns that come with it. Lehmann et al. (2022, p.3431) showed that algorithmic transparency is not a simple variable that is only about making the algorithmic process more clear. Different levels of transparency take place in different contexts, leading to different perceptions.

In some cases transparency does not always help and can even backfire, hurting people's perception. Lehmann and colleagues (2022, p.3431) furthermore show that when the algorithm is perceived to be simpler than what was thought, it negatively affects how people view it because they are disappointed in the algorithm. This negative effect is not the case for more complicated algorithms. Even if users do not completely understand how the algorithm works, the perceived difficulty does not lead to a more negative view. Thus, algorithmic transparency is only helpful when working with an algorithm that is not perceived as disappointingly easy by users. Saragih and Morrison (2022, p.1236) on the other hand have proven the contrary, when they found that providing people with relevant information about how the algorithm works encourages greater acceptance of the algorithm. Transparency about both how the algorithm works and functions, as well as information on how the algorithm has previously performed, led to more acceptance of the advice and decisions from the algorithm (Saragih & Morrison, 2022, p.1235). Thus, by providing more information on the algorithm people were more comfortable with trusting the decisions made by the algorithm and perceived it to be better. However, this study did not test for different levels of transparency, which could make a difference as previously shown and is thus important to note. It did take into account the effect of different levels of previous performance on user perception and found that perception was highest when the algorithm had performed better in the past (Saragih & Morrison, 2022, p.1233).

Algorithmic transparency is closely linked to knowledge, because the more transparent an algorithm is, the more users know about how it works. Araujo and colleagues (2020, p.621) have shown that knowledge about AI increases users' expectations about the usefulness of decision-making processes. People with more knowledge about the AI system are more optimistic about automated decision-making processes and deem it to be more useful than people who know less about the process. Important to note is that more knowledge had less of an influence on people's risk perceptions (Araujo et al., 2020, p.618). Knowledge therefore mostly affects how useful people perceive the decisions made by the AI system, and does not increase people's risk perception of the AI system. If people have more knowledge of how the AI system works, their perception will increase. The findings by Araujo and colleagues (2020, p.621) are in line with the algorithmic appreciation theory, which describes that "people adhere more to advice when they think it comes from an algorithm than from a person" (Logg et al., 2019, p.90). Consequently, this means that decisions by AI are valued better than decisions taken by human experts. This is especially the case in specific contexts such as media, health and justice when compared to general attitudes of AI. However, for justice and health, human experts were perceived to be less trustworthy and for media this difference was not significant.

Based on this information, the first hypothesis has been made up:

H1 Greater knowledge of privacy implementations in artificial intelligence use will lead to a more positive perception of AI.

The (Moderating) Impact of Context

AI systems are used for many different things and often in diverse contexts. In these different contexts, data with varying forms of importance are used, leading to different concerns. Some data is simply more valuable than others and should be better protected. Thus, a focus on personal data use of AI in different contexts is needed.

Privacy has been an issue associated with information technologies for a long time (Nissenbaum, 2004, p.119). Since AI has become more popular in recent years, this has become an even more pressing issue. Because the AI systems need to be trained on existing data, privacy issues have become an important focus point. However, since they are used in many different contexts for many different applications, there are different levels of privacy issues. This ties in with contextual integrity, which is about the fact that adequate privacy protection needs to be adjusted for the context (Nissenbaum, 2004, p.155). Information gathering and dissemination need to be appropriate to the context that they are used in and obey the norms of this specific context. Whether something is considered a violation of privacy depends on multiple variables. The first one is related to the context, in this case, the context in which the AI system is used. The second variable is about the nature of the information in relation to this context. Next to this, other variables such as who receives the information, their relationship to the information subjects, the terms on which the information is shared by the subject and if, how and where the information is further shared. The focus in this case is on inappropriate flows of information, which relate to information flows that violate context-specific informational norms (Nissenbaum, 2018, p.839). Because personal data is used by AI in many different contexts, the information must flow according to the contextual norms. Context is therefore an important factor that has to be taken into account when looking at the use and perception of AI, and this link will be specified in Hypothesis 3.

Dorotic et al. (2024, p.127) demonstrated that the context in which an AI model is used matters for how users perceive it and how likely they are to adopt it. People evaluate the costs and the benefits of the AI model and the results of feeling served versus feeling exploited when using it in their lives. These evaluations differ across contexts because different models are used in different settings. Dorotic and colleagues (2024, p.127) show that in commercial applications, users are more likely to emphasize the benefits of efficiency and personalization and focus less on the personal costs, for example, that their privacy is harmed. When the personal costs are more important, however, perceptions get worse. This is specifically the case when AI technologies appear intrusive on users' civilian liberties and privacy (Dorotic et al., 2024, p.128). Furthermore, people are more willing to share their personal data with firms when they perceive a better fit between the type of data that is collected and the purpose. In a public context, this is only sometimes the case, however, as people do not want to be monitored constantly as it can become intrusive to their civilian liberties and privacy (Dorotic et al., 2024, p.128). Hence, the context in which the AI model is applied matters because people calculate the perceived benefits and costs differently. Saragih and Morisson (2022, p.1234) found that people were more willing to accept algorithmic advice in high-stakes contexts, for example in situations they felt were important. When the accuracy of the algorithm increased, algorithmic acceptance was higher in important situations than in situations with relatively low stakes. This is an interesting effect because it shows that if an algorithm performs correctly, people are more likely to accept it in situations that they perceive to be important, thus making it extra important to look at it in this study. However, as was previously shown in studies on algorithmic appreciation there is a very thin line here because as soon as there is more focus on the algorithm's error, appreciation decreases (You et al., 2022, p.358). This effect will therefore also be further explored in Hypothesis 3.

Perceptions of privacy are closely related to privacy fatigue. Choi and colleagues (2018, p.43) define privacy fatigue as "a psychological state of tiredness with the issue of online privacy so that it encompasses other relevant concepts, and further, empirically demonstrate its role in online privacy practices". Thus, it means that even though people might be willing to take action to protect their privacy, they are sometimes too fatigued to do something about it because it is too difficult to find out exactly what they need to do. Even in the case where they do know this, it can be hard to make decisions because they are not informed enough and do not know what everything means. Because of this fatigue, they simply take the easiest route and choose to do nothing. This phenomenon has been studied for Internet of Things (IoT) users, where Oh and colleagues (2018, p.31) have shown that low knowledge of the security of the system led to an increase in privacy fatigue. IoT users were not familiar with the privacy protection methods and were not familiar with the aspects, causing them to either overestimate or underestimate threat assessments. Consequently, they did not try to do anything to protect their privacy because they did not know how to do it. Next to this, they showed that privacy fatigue can occur differently depending on the purpose of the IoT device and the environment it is used in (Oh et al., 2018, p.31). Users of smart healthcare systems may become insensitive to the continuous sharing of their personal data, leading to a greater chance of privacy fatigue. These systems are used daily, and if they are continually used without thinking about the effects, even sensitive medical data can be shared easily and unsecured because privacy fatigue is very likely to take place. Privacy fatigue has thus been proven to take place for users of IoT devices, but no research has been done yet in combination with AI systems. However, because these are similar systems and not a lot of information is known about how steps can be taken to protect one's privacy in AI systems, privacy fatigue will likely happen to users of these systems too. Next to this, the different contexts in which AI systems are used might lead to different levels of privacy fatigue. Similar to the use of smart healthcare systems, in a medical AI context privacy fatigue might be greater because people find it more difficult to deal with their information being used by the AI systems than when they deal with less sensitive information in a different and easier perceived context such as entertainment. This connection between context and knowledge will be further explored in Hypothesis 2.

Closely connected to privacy fatigue is the privacy calculus theory, which is about the calculation of privacy benefits and costs (Gerber et al., 2018, p.229). This theory explains how when the expected benefits of using something outweigh the costs of it, users are expected to willingly give up their personal data. In the context of this paper, it means that users constantly try to balance and calculate what is most important to them: the perceived benefits of using the AI model and all the advantages it leads to, or the possible costs that come with using the AI model, and the consequential disadvantages that come with it such as loss of personal information. Generally, users who continue to use the AI model, even when they have adequate knowledge of the costs, perceive it to be so valuable that nothing can stop them from using the model and giving away their data. Naturally, the benefits and costs vary in different situations with more or less knowledge about the model and various contexts, which can lead to different calculations. The phenomenon has already been studied in the public service domain, where it has been proven that the privacy calculus theory plays a role in people's decision-making process of whether to use the AI system or not (Willems et al., 2023, p.2128). In this case, users had to calculate how beneficial the AI-driven app was that they were told to download and use. Because the app was related to a public service domain, the trade-off was less important because personal data does not have the same value for a public service organisation as for a profitable organisation. In the public service domain, personal data is even more likely to be used to improve the service which has a potential extra and indirect benefit for all citizens. The main concern in this case was thus less related to the potential economic benefit, but more to the service experience and the overall public value. However, there is still a chance that data is used for the wrong purposes, so a privacy calculation still has to be made for every user. To improve the information about this combined phenomenon of knowledge leading to privacy calculations in other AI contexts as well, this study will do further research on this theory, specified in Hypothesis 2.

Because AI is used in many different industries, each with a different amount of impact and also a different kind of data and different amount of data that is used, the influence of context will be taken into account in the current study. Personal data about which movies and series someone likes, for example, is less serious than personal data regarding someone's health and what kind of medical problems they have. Because of the difference in importance, there is likely also a difference in how people perceive their data being used by the different AI models. Health data is simply more sensitive than someone's entertainment preferences. Filiz et al. (2023, p.1) have studied the extent of algorithm aversion in situations with varying importance, some with potentially serious consequences and others with only trivial consequences. Even when algorithms have been proven to be more efficient and better than humans, and would therefore be the preferred chosen option because the results are better, there are still a lot of cases where people dislike the algorithm and would rather trust a human's decision. Especially in cases with potentially serious consequences, where it is extra important that the right decisions are made, algorithm aversion still took place in half of the cases (Filiz et al., 2023 p.17). In more low-stakes scenarios algorithm aversion only took place in about 30% of the cases. Thus, algorithm aversion occurs more frequently when the consequences of a decision are more serious. Because of the interesting addition of low-stakes and high-stakes contexts and their consequences on perception, this topic will also be taken into account in this study in Hypothesis 3.

Based on the information stated above, the following hypotheses are proposed:

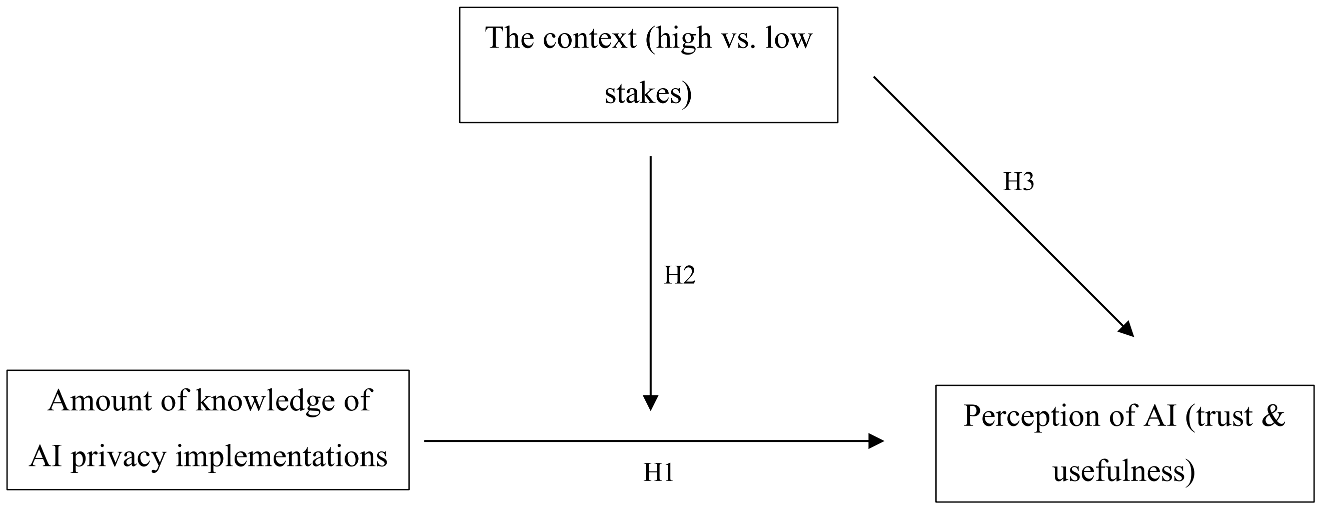
H2 The importance of the context (high- vs. low-stakes) moderates the relationship between knowledge of privacy implementations in artificial intelligence use and people's AI perception, with the effect being stronger in a low-stakes context than in a high-stakes context, leading to more positive perceptions of AI in a low-stakes context than in a high-stakes context.

H3 AI privacy deployment in low-stakes contexts will lead to a better AI perception than in higher-stakes contexts.

The hypotheses are summarized in a conceptual model in Figure 2.1.

Figure 2.1

Hypothesised conceptual model



3. Methods

Explanation and Justification of Methods

The study was done with quantitative methods. This type was chosen because it made it easier to generalise the results and minimise the researcher bias in data collection and analysis. The study was carried out with an experiment because it is the best way to measure the difference in how people feel about their privacy in AI in different situations. Furthermore, causality could be studied to find out whether the different levels of the independent variable caused an effect on the dependent variable (Neuman, 2014). The research question set out to find whether there was a difference in privacy perception when people have more or less knowledge of AI privacy implementations and whether this difference occurred in different contexts, with high stakes and low stakes. An experiment was done to compare the different situations and find out where the perceptions of AI differed.

The experiment was done with a survey on Qualtrics because it was easy to distribute and worked well with the chosen research design. Qualtrics' design made it possible to create different stimulus materials and distribute them to the participants evenly. Furthermore, all of the other steps that were included in the experiment, such as the informed consent, questions about demographics and the attention check were also easily added to the survey. The final data was downloaded from Qualtrics in an SPSS file after which it was ready for analysis.

Procedure

After clicking the link for the survey, participants were redirected to the questionnaire on Qualtrics. They were first shown the informed consent, where they were informed about the study, how long it would take and how their data would be handled. After agreeing with this they were taken to the actual study. The first question asked them to rate their own knowledge of AI because this is an important topic of the study and could potentially influence the effectiveness of the manipulation. If participants already had high knowledge of the topic and were taken to one of the 'low knowledge' conditions, this could influence how the manipulation worked for them because it might not work as it was intended. Therefore, this question was asked at the beginning to account for this. After this question, they were randomly shown one of the four stimulus materials. They were asked to read the text thoroughly after which they could continue to the next page. They had to stay on the page for at least 30 seconds. After 30 seconds the button appeared that they could click to continue to the next page. They were then presented with questions about the dependent variable to measure their perception of AI. The next pages contained the attention check and manipulation check, which measured if they were paying attention to the study and the stimulus materials respectively. The survey finished with questions about the participants' demographic characteristics. In the end, they were debriefed about the goal of the study and presented with more information about how AI is used in the contexts that were presented to them in the stimulus materials in case they wanted to know more about the topic. After they submitted the survey they were thanked for their participation.

Sample and Sampling Strategy

The units of analysis in this study were people over the age of 18 who spoke sufficient English to be able to follow the study. There were no further special requirements to participate in the study. These two requirements were used because participants had to be able to give their consent to participate in the study, and they had to be able to correctly understand everything so that their answers would be reliable. Because the requirements were not very strict, the sample could be quite diverse. The design consisted of four different conditions, with a necessary amount of at least 30 people per group to follow the guidelines of the Central Limit Theorem (Islam, 2018, p.6). Therefore, the sample size had to consist of at least 120 participants. The final amount of participants was 131. Participants' ages ranged from 19 to 59 (M = 25.95, SD = 8.03). 36 men were included in the final sample (27.5%) and 95 women (72.5%). Most participants finished a university bachelor's degree (47.3%), with a university master's degree (19.1%) and HBO degree (16.0%) as the second and third most frequent education levels. Most participants resided in the Netherlands (71.8%), but participants also resided in other countries such as Belgium (6.9%), the United Kingdom of Great Britain and Northern Ireland (5.3%), Switzerland (3.1%) and more.

To be included in the final sample, participants had to be over the age of 18, finish the entire survey and answer the attention check correctly. The attention check was included in the study to increase validity and measure if people were paying proper attention while filling in the survey. If they did not correctly fill in this question it is not clear if they paid attention and their answers are therefore not reliable. Furthermore, participants whose answers seemed unreliable were also excluded. This was mostly the case for straightliners, participants who filled in the same answer for every item in the dependent variable measurement scale. They were excluded if they did this for both the perception of AI scales as well as the manipulation check scales. In certain cases, participants filled in the same answer for all of these items. This makes their answers unreliable because it is unable to tell whether they actually paid attention to the question or just wanted to go through the survey as fast as possible. For this reason, they were excluded. Next to this, a check for speeders was done. The general rule was abided by and participants who were faster than 30% of the median duration were taken out. No one was that fast, so this was not necessary. Participants who adhered to all aforementioned requirements were included in the final dataset.

Participants were recruited in multiple ways. Firstly, they were collected via convenience sampling. Next to this, the survey was posted on the websites SurveyCircle and SurveySwap (SurveyCircle, n.d.; SurveySwap, n.d.). These websites were a reliable way of collecting participants. They are designed for people to swap their surveys with each other under careful rules that make sure that people fill it in truthfully and with care. Furthermore, the survey was also published in various Facebook groups for survey swaps. These are also carefully checked by the group leaders to make sure that people abide by the rules to only post about survey studies, only participate in studies where they match the requirements and more. This helped to make sure that the participants who were recruited from here were also reliable. The various ways of collecting data are thus a reliable way of collecting a diverse sample who filled in the survey with great care.

Operationalisation

Before participants were presented with the stimulus materials, they were asked about their knowledge of AI. This was done with the following question: *How would you rate your knowledge of AI?* Participants were given seven answer options, rating from 'Very good' to 'Very poor' and also included an 'I don't know' option for participants who could not rate their own knowledge on this scale. This question was included because it measured participants' knowledge easily and understandably. If the question was too difficult, participants might have become suspicious of the goal of the study or would not have been able to understand or answer the question. Because people need to judge their own knowledge the answers might not be completely valid, but this was deemed not too big of an issue because it was not one of the main variables. The measurement of perceived knowledge of AI is very new and no reliable scale has been made to measure this variable yet. Therefore, the decision was made to measure it via a single-item scale. This variable is not the main focus point of the study and it is not one of the key variables. It is furthermore an easy concept that does not need multiple items because this would only make it more difficult to measure and more difficult for participants to fill in (Allen et al., 2022, p.2).

Doing it this way helped it to be an efficient way of measuring and processing this variable in the rest of the survey and the analysis, which is why it was deemed sufficient enough to use a single-item scale.

The dependent variable perception of AI was measured with two variables: trust in AI and usefulness of AI. This decision was made to make the variable easier to measure. Trust and usefulness have been studied together before and shown to be useful variables to measure perception (see Araujo et al., 2020; Luo & Lee, 2011; Mou et al., 2017). Both variables were measured with adaptations from previous scales to ensure reliability. Trust in AI was measured on a 7-point Likert scale with points going from 'Strongly disagree' to 'Strongly agree'. It was measured with three items that were adapted from the study by Shin et al. (2022):

I trust the recommendations by this AI platform.

Recommended results via this AI process are credible.

These AI personalized results are dependable and trustworthy.

Usefulness of AI was also measured with a 7-point Likert scale, ranging from 'Strongly disagree' to 'Strongly agree'. This variable was measured with five items, adapted from a study by Davis (1989) and a study by Nysveen and colleagues (2005):

Using this AI saves time.

Using this AI improves efficiency.

This AI is useful.

This AI increases productivity.

This AI improves the quality of the recommendations.

Next to the questions about the variables, participants were also asked questions about themselves. Demographic questions such as age, gender, education level and country of residence were asked to get a clear overview of what kind of participants filled in the survey. This also helped to check whether the different population groups were equally distributed.

Furthermore, extra questions were added to the survey to check whether the participants were paying attention while filling in the survey. Firstly they were asked to answer an attention check. They were shown a scale going from 'Strongly disagree' to 'Strongly agree' and were asked to answer 'Agree'. If this was answered correctly, it could be concluded that they were paying attention. If this was not the case, they would be excluded. The second check was the manipulation check, to check if the manipulation worked as it was intended. This was measured with two questions, one to measure if participants correctly understood the context and one to measure if they were correctly able to recall the amount of information, and thus the knowledge that was shown to them. The question to measure the context was as follows: *In the text that you read, in which context was AI used?* The answer options for this question included both conditions, as well as the option to specify something else, the option that they did not know it anymore and the option to select 'Spotify music recommendation'. The last option was added to make it less obvious which one they had seen and make the answers more reliable. The amount of knowledge recall was measured with multiple items, for which participants had to answer on a 7-point Likert scale ranging from 'Strongly disagree' to 'Strongly agree' how much they agreed with the type of personal information being used by AI in the text that they had read. The items were as follows:

your age.

your gender.

your location.

And give you the ability to opt out of your information being used.

The different options were added to get a clear overview of how much participants remembered after reading the stimulus materials, and thus how well the manipulation worked for them.

Stimulus Materials

The independent variable of this study is the amount of knowledge of AI privacy implementations. This variable consisted of two levels: high knowledge, where people know a lot about how AI systems deal with their privacy and what kind of personal information it uses, and low knowledge where people know nothing about how AI systems deal with their privacy and what kind of personal information it uses. The information that was stated in the high knowledge condition was influenced by the Digital Services Act, and information was added such as that people were able to opt out of their information being used and information on why they are recommended certain information (The Digital Services Act (DSA), n.d.). In the low knowledge condition, this was left out to make the difference between the conditions as big as possible. The moderating variable of this study is context, which was about the context in which the AI system was used. This variable also consisted of two levels, a low-stakes context in which the personal information that is used by the AI system is not very important and a high-stakes context in which the personal information used by the AI system is more important. The low-stakes context consisted of information about Netflix and what kind of information it uses to provide someone with the best recommendations. Here, it was mainly about what movies someone likes and which genre they watch the most. The high-stakes context was an explanation of how an AI system can be used to diagnose diseases, and what kind of information it uses for this such as personal information on someone’s health, condition or medical history. This is more personal and has more value and is thus related to a context with higher stakes. The decision to compare a media context such as Netflix and a medical context such as disease diagnosis was based on a previous study by Araujo et al. (2020, p.615), where they compared a media context to a medical context and a justice sector context. The media context and medical context were thought to be the most opposite regarding low and high stakes, so the decision was made to use these two for the stimulus materials for the current study. Furthermore, a separate study by Fritsch and colleagues (2022, p.1) focused on the perception of AI in healthcare and took previous knowledge into account, which is similar to what this study aimed to do. This enhanced the decision to use the healthcare context for the high-stakes condition instead of justice, which was also used in the study by Araujo et al. (2020) and deemed high-stakes, but less relevant to the current study. Because of this information from previous studies, these two specific contexts were chosen to be included in the stimulus materials.

Even though all conditions are different and include different information, they were all designed to be of equal size and similar layout. The high knowledge conditions included bullet points that put extra emphasis on the personal information points used by AI and the low knowledge conditions included extra information about the context itself that did not focus on AI. This was done so that the results were more credible and perceptions of AI could be better compared among the four different conditions.

The two variables amount of knowledge of AI privacy implementations and context in which the AI system is used were combined into stimulus materials to be able to test the dependent variable. This resulted in four different stimulus materials. The first condition, high knowledge and low stakes, included a text about how Netflix uses someone’s personal information to provide personal recommendations for films and series. This text briefly explained what Netflix is and then continued to explain specifically how it uses AI and what kind of information the company uses from someone, such as someone’s age and location. The personal information that was used was put in bullet points to emphasize the information. Most of the information was true and taken from Netflix’s own website (Netflix, n.d.). Some information about which personal information was used was added to the text to make it resemble the other condition better. The first three points, age, gender and location, were included to be similar to the other high knowledge condition. The second point was specifically relevant to this context. The last point referred to someone's viewing history on the platform. This was also context-specific but could be adapted to be similar to the other high knowledge condition.

The next condition was low knowledge and low stakes. This text also explained how Netflix worked, but included more detail about the platform itself with basic information about films and series. This was necessary because this condition did not include details on what kind of personal information was used. To make sure that the texts from each condition were equally long, this condition needed more information on other subjects. Therefore, more information was included that was not relevant to the study or the participant. Very basic information was included such as what Netflix is and what it offers.

The third condition, high knowledge and high stakes, was about the use of AI in a medical case by a doctor. This text explained how AI can be used to diagnose diseases and what kind of personal information is necessary for this. Similar to the Netflix condition, the information was taken from real life (Kumar et al., 2022, p.8478-8479). To make the text as similar as possible to the other high-knowledge condition, it was designed in the same way. At first, an introductory explanation text was given, after which the personal information was laid out in bullet points for emphasis. A concluding sentence was added at the end. Even though the information about the context was different, the design was still the same. The personal information points that were presented to the reader were also mostly the same. The first three information points were exactly the same, with age, gender and location. The fourth point was adapted to this specific context. The last point focused on the history of the context, which was in this case someone's medical history.

The fourth and last condition was about low knowledge and low stakes. In this condition, participants were presented with a text about how AI is used in diagnosing diseases. However, because this is a low-knowledge condition, they were not told any specific details. To be of roughly the same size as the other high knowledge condition, more information was included in this case about how a doctor works and how they can help someone when they are ill. The design of this condition was similar to the other low knowledge condition, a single paragraph with the same structure. Even though the context was different, the same topics were addressed such as a brief explanation of how AI can be used in this context and how the context itself is established and what it is used for.

Even though the stimulus materials in each condition were different, they were designed to be as similar to each other as possible to reduce the risk of anything else influencing the results of the study. Careful consideration was taken to design them in the best way possible. Deception took place because not all conditions included the exact truth of how AI is used in a specific context, but participants were presented with the correct information at the end of the survey during the debriefing. An overview of the scenarios presented to the participants can be found in Table 3.1. Additionally, an example of how the stimulus materials were presented to participants is shown in Image 3.1.

Table 3.1

Overview of the stimulus materials in each condition

	Low-stakes context	High-stakes context
Low knowledge	Informative text about Netflix with little focus on AI and the information it uses.	Informative text about medical diagnosis possibilities with little focus on AI and the information it uses.
High knowledge	Informative text about Netflix with a big focus on AI and the information it uses.	Informative text about medical diagnosis possibilities with a big focus on AI and the information it uses.

Image 3.1

Example of stimulus material as presented to participants

You will now read a text which explains how Netflix uses AI. Please read it carefully. After 30 seconds you will be able to continue to the next page.

AI use by Netflix

Artificial intelligence (AI) can be used in many aspects of daily life. An example of this is the recommendations of films and series on Netflix. When you use Netflix, multiple information points about you are collected and used to create a personal home page that best fits your interests. The company does this to make it as easy as possible for you to find a good film or series that it thinks you would like. It uses a type of artificial intelligence, called a machine learning algorithm, specifically a recommender system. This system uses your personal information to find the best recommendations for you. It includes information such as:

- Your age
- Your gender
- Your location
- At what time you are watching
- Your personal viewing history

Netflix only uses your private information to provide you with the best recommendations on the platform, they are not used by anything or anyone else. You can always opt-out or change the amount of information being used.

Reliability and Validity of the Study

The reliability of the study was accounted for in several ways. First of all, Qualtrics was used to create the survey. This is a reliable platform to make surveys and collect data and works well and clearly. It helps participants to easily understand the questions and fill them in. Next to this, all scales were taken from previous studies and adapted for the current study. They have been proven to work and could therefore also work well for this study. All steps of this study were clearly described, so it could be replicated if needed. All participants in the study were treated similarly and equally, resulting in an even further increase in reliability. Furthermore, reliability tests were conducted, of which the results can be seen below.

The internal validity of the study was quite high, because of multiple reasons. Firstly, the stimulus materials were randomly and evenly presented to the participants. This made sure that the results from the study and differences in people's perceptions could be measured and so that other explanations could be ruled out. Furthermore, the stimulus materials were designed to be as similar to each other as possible. The text in each condition was designed to have almost exactly the same length as well as the same layout. A timer was placed together with the stimulus materials to ensure that participants could only continue to the next page after 30 seconds. This increased the chances that they had thoroughly read the stimulus materials and were able to answer the next questions well-informed with the information that was presented to them. Next to this, people's knowledge of AI was measured before the study. If they already knew a lot about AI this could potentially be a confounding variable. Therefore, it was measured at the start of the survey and could be included in the analysis if necessary.

The external validity of the study was also quite high. A pre-test was done before the survey was sent out, to check whether everything was measured in the way it was intended to and to make sure that it was clear enough. The participants of the study were demographically varied and had different ages, genders, and education levels. The sample, and thus the results of this study, can therefore easily be generalized to a wider population.

Processing and Analysis of Data

When the necessary amount of participants was reached, the data was downloaded from Qualtrics in an SPSS file so that it could be analysed in SPSS. Before the real analysis could be done, preparatory steps were taken. The first step was to clean the data. Participants who did not finish the survey or who did not adhere to the requirements were excluded from the study. Next to this, participants who did not correctly answer the attention check were also excluded. This brought the total number of participants down from 154 to 131. Furthermore, missing variables and outliers in the data were also accounted for. When all preparatory steps were done, a randomization check was done to check whether all conditions were equally distributed among the participants. Further testing was done by doing a factor analysis to check whether all items correctly corresponded to the same scale. It was tested for reliability with Cronbach's alpha.

After all these steps were taken, the hypotheses could be tested. This was done with a two-way ANOVA test. This test was chosen because it seemed to be the best one for the current research design. It allows for the comparison between two different independent variables and their effect on the dependent variable. Because this research included a moderator variable, this test was thought to be the most fitting.

Pre-Test

A pre-test was done to check whether the survey worked as intended and if everything was clear. It also checked whether the results were as expected and if the manipulation check worked. A total of 9 participants filled in the survey for the pre-test. 4 males (44.4%) and 5 females (55.6%) filled it in, with ages ranging from 19 to 57 (M = 30.11, SD = 14.30). After looking at the results, the wording of the manipulation check was slightly changed to make it clearer. There was no further feedback as participants found it very clear. Thus, the survey was deemed good enough to be used for the study.

Research Ethics

Experimental studies come with risks, and this thesis is just the same. The main ethical considerations of this research are because of the experimental design. Firstly, participants were not told that they were participating in an experiment. They were also not told about the details of the purpose of the study. This information was intentionally withheld from them because it could possibly influence their perception. Furthermore, active deception took place in the stimulus materials, because the information that was presented to the participants included fabricated information to make them more similar. The deception was justified because the benefits outweighed the risks, it did not cause physical pain or severe emotional distress and participants were debriefed at the end of the study (Gravetter & Forzano, 2012, p.85). At the beginning of the study, participants were presented with an informed consent form which included all necessary components (Gravetter & Forzano, 2012, p.83). Because this consent form partially deceived participants, a debriefing was included where people were presented with the complete purpose of the study and correct information on the stimulus materials. The debriefing included links to the pages where the information was taken from in case they wanted more information about the topic.

The experiment took place online, with participants filling in an online survey. This brought risks but also ensured privacy. Maintaining confidentiality in an online setting is easier than a paper survey because the data cannot be lost and accidentally get to the wrong people (Fowler, 2014, p.142). Further steps were taken to make sure that people could not be personally identified based on their answers and that anonymity was ensured (Treadwell, 2017, p.50). Only informative demographic information was gathered in the data collection process, but names and other personal information were not collected. The data file was further carefully guarded to ensure that no one besides the researcher had access to it.

Factor Analysis

The eight items of the dependent variable perception of AI which were Likert-scale based were entered into an exploratory factor analysis using Principal Components extraction with Direct Oblimin rotation based on Eigenvalues (>1.00), $KMO = .88$, χ^2 (N = 131, 28) = 655.64, $p < .001$. The eight items resulted in two factors, trust in AI and usefulness of AI. However, all items had high reliability together ($\alpha = .90$) and were designed to be combined into one variable. Reliability would not increase if any of the items were deleted, so the decision was made to include all items in one variable called 'Perception of AI'. Together, all eight items explain 74.3% of the variance in 'Perception of AI'. The factor loadings of each individual item in the variable are presented in Table 3.2.

Table 3.2

Factor loadings, explained variance and the reliability of the two factors found for the scale 'Perception of AI'

Item	*Trust in AI*	*Usefulness of AI*
Recommended results via this AI process are credible.	1.00	
These AI personalized results are dependable and trustworthy.	.87	
I trust the recommendations by this AI platform.	.77	
This AI improves the quality of the recommendations.	.57	
Using this AI saves time.		.81
Using this AI improves efficiency.		.75
This AI is useful.		.74
This AI increases productivity.		.66
R^2	61.56	14.25
Cronbach's α	.91	.84

Manipulation Check

After the factor analysis, a manipulation check was done to check whether the stimulus materials worked as they were intended. This was done with a crosstabulation test. Participants correctly stated in which context the text that they had read took place (χ^2 (1, N = 131) = 123.12, $p < .001$). Furthermore, they were also correctly able to state how much information the AI system used, thus correctly showing whether they had high or low knowledge about it. This was the case for age (χ^2 (6, N = 131) = 27.63, $p < .001$), gender (χ^2 (6, N = 131) = 19.28, $p = .004$), location (χ^2 (6, N = 131) = 13.11, $p = .041$) and the opportunity to opt-out (χ^2 (6, N = 131) = 16.85, $p = .010$). Based on these results, it is clear that the manipulation across all conditions was successful.

Randomisation Check

After the manipulation check, a randomisation check was done to check whether the variables age, gender, level of education and previous knowledge were equally distributed across the conditions. The randomisation check for the variable age was done with a one-way ANOVA. The results are not significant, F (1,127) = .12, $p = .948$, meaning that the different ages are spread evenly across all four conditions. The randomisation of the variables gender, education level and previous knowledge were tested with a crosstabulation test. The results of all tests were not significant, indicating that gender (χ^2 (3, N = 131) = 2.85, p = .416) and education level (χ^2 (12, N = 131) = 10.89, p = .538) and previous knowledge (χ^2 (12, N = 131) = 13.78, p = .315) were spread equally across the conditions. Based on these results, it can be concluded that the randomisation was successful. Because previous knowledge was equally distributed across the conditions, it also meant that it did not need to be included as a potential confounding variable in the final analysis for the hypothesis testing.

4. Results

Hypothesis Testing

Effect of Knowledge of AI Privacy Implementations on Perceptions of AI (H1)

A two-way ANOVA test was done to test the hypotheses for the main and interaction effects, with knowledge of AI and context of AI as independent variables and perception of AI as dependent variable. A Levene's test was done and the assumptions were met, meaning that there is no difference in the equal variances of the population as the test was not significant. A check for normality was done with measures of Skewness and Kurtosis, and the assumptions of these tests were met because the values were between -3 and +3. The results showed that perception of AI was slightly higher when participants had less knowledge (M = 5.33, SD = .90) than when they had high knowledge (M = 5.28, SD = .89). However, this difference was too small to be significant, F (1,127) = .17, p = .682, η^2 = .00. This means that the amount of knowledge of AI does not significantly influence perceptions of AI. H1 is therefore rejected.

Moderating Effect of AI Context on the Relationship between Knowledge of AI Privacy Implementations and Perceptions of AI (H2)

The moderation effect of context in which the AI system is used on the relationship between knowledge of AI privacy implementations and perceptions of AI was also tested with the two-way ANOVA test that was previously done. These results also show a small difference in perception, where the perception of AI is slightly higher in a low-stakes context (M = 5.34, SD = .85) compared to a high-stakes context (M = 5.27, SD = .93). The highest perception of AI was measured for the low knowledge and low-stakes context condition (M = 5.53, SD = .66). After this, the opposite condition with high knowledge and a high-stakes context reached the highest measured perception of AI (M = 5.39, SD = .79). The second to last condition was the high knowledge and low-stakes context condition (M = 5.17, SD = .97) with the lowest measured perception of AI in the low knowledge, high stakes context condition (M = 5.15, SD = 1.05). The difference between each condition was not big enough to be significant, F (1,127) = 3.81, p = .053, η^2 = .03. The second hypothesis is therefore also rejected. It should be noted however that the effect is very close to significance and should be carefully considered in different settings.

Effect of AI Context on Perceptions of AI (H3)

The direct effect of the type of context in which an AI system is used on the perception of AI was also measured in the two-way ANOVA test. This relationship is also not significant, F (1,127) = .29, p = .594, η^2 = .00. Though the perception of AI is slightly higher in a low-stakes context (M = 5.34, SD = .85) than in a high-stakes context (M = 5.27, SD = .93), the difference is not big enough to be significant. The last hypothesis is thus also rejected.

An overview of the mean perception of AI in each condition can be found in Table 4.1 and Figure 4.1.

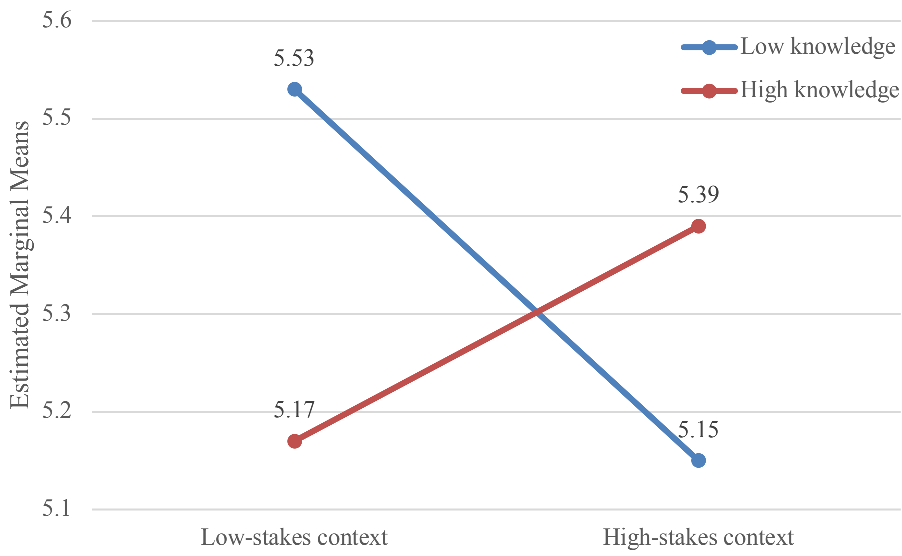
Table 4.1

Means (and standard deviations) of each hypothesis for perception of AI, trust in AI and usefulness of AI

Hypothesis	Knowledge	Context	**Perception**	**Trust**	**Usefulness**
H1	Low		5.33 (.90)	4.86 (1.21)	5.80 (.82)
	High		5.28 (.89)	4.86 (1.03)	5.69 (.91)
H2	Low	Low-stakes	5.53 (.66)	5.33 (.63)	5.73 (.80)
		High-stakes	5.15 (1.05)	4.42 (1.44)	5.87 (.84)
	High	Low-stakes	5.17 (.97)	4.85 (1.03)	5.48 (1.01)
		High-stakes	5.39 (.79)	4.88 (1.04)	5.90 (.75)
H3		Low-stakes	5.34 (.85)	5.08 (.89)	5.61 (.91)
		High-stakes	5.27 (.93)	4.65 (1.26)	5.88 (.79)

Figure 4.1

Estimated marginal means of perception of AI across all four conditions



Supplementary Analysis

To account for the Type II error of accepting a null hypothesis when it is actually false, a power analysis was done to estimate the power of the results. The decision to do this test was made because even though the results show no significance, they do show a very interesting and possibly useful insight. With the current sample, the resulting power is 45.6%. Considering that a statistical power of 80% or more is needed to accept the results, this is very low. Similar studies such as the one by Logg et al. (2019) on algorithm appreciation, had a much higher power of 99.9% and found significant results. Thus, the power of the current study is very poor, compared to previous literature. Results of the power analysis further indicated that the required sample size to achieve 80% power for detecting a medium effect, at a significance criterion of $\alpha = .05$, was $N = 268$ for the ANOVA test. This would mean 67 participants per condition, instead of the approximately 33 that were included now. The current sample followed the guidelines of the Central Limit Theorem which states that each group should consist of at least 30 participants (Islam, 2018, p.6). The power analysis showed that with a bigger sample, stronger effects would be able to be detected as the sample would be a better estimate of the population. Thus, the power analysis shows that if a different approach were taken regarding the data, different results might show up. Because of this, supplementary analyses were done to find out how the results might be impacted in different situations.

As previously explained, speeders were accounted for in the analysis. The median duration that participants needed to fill in the survey was 191 seconds. Participants who were finished in 30% of this time or less had to be excluded. This was not necessary because no participant was that fast. However, there was someone who was done after 89 seconds. This is also relatively fast, considering that participants had to look at the stimulus material for at least 30 seconds. To see how this would influence the results, a separate test was done where the answers from this participant were taken out. The results do not change much for hypothesis 1 and hypothesis 3, because they are still not significant. However, the moderation effect of hypothesis 2 became significant in this case. An overview of the different results can be seen in Table 4.2.

The highest perception of AI was still measured for the low knowledge and low-stakes context condition (M = 5.53, SD = .66). Perception in the condition with high knowledge and a high-stakes context increased (M = 5.43, SD = .77). The other two conditions also stayed the same, (M = 5.17, SD = .97) for the high knowledge and a low-stakes context condition and (M = 5.15, SD = 1.05) for the low knowledge and high-stakes context condition. Because of the change, the moderation effect of hypothesis two was significant, F (1,126) = 4.38, p = .038, η^2 = .03.

These results show how easily influenced the results are. One participant who filled in the survey very fast was able to change the significant p-value for the interaction effect from p = .053 to p = .038. Because this person was shown the stimulus material for the high knowledge and high-stakes context, these values are changed in this output of results. The mean increased, creating a bigger contrast between the low knowledge and low-stakes context condition and the high knowledge and high-stakes context condition towards the other two conditions, which were a combination of them. All of this was possible because of the answers of one person. The p-value is very influenceable and it is therefore important to also look at other factors, such as the mean plot.

Table 4.2

ANOVA results for the moderation effect in the primary analysis and supplementary analysis

Type of Analysis	Variable	*df*	*F*(1,126)	η^2	*p*
H2 (excluding speeder)	Knowledge	1	.08	.00	.783
	Context	1	.16	.00	.691
	Knowledge * Context	1	4.38	.03	.038
		df	*F*(1,127)	η^2	*p*
H2 (including speeder)	Knowledge	1	.17	.00	.682
	Context	1	.29	.00	.594
	Knowledge * Context	1	3.81	.03	.053

Supplementary Testing of Dependent Variables Trust in AI and Usefulness of AI

The dependent variables trust and usefulness were originally intended to be combined into the variable perceptions of AI. As previously shown, these results were not significant. However, because the factor analysis originally resulted in two variables with high reliability and because the original results for perception of AI as a whole are not significant, the variables trust in AI and usefulness of AI will also be tested separately. Perception of AI was measured with two separate scales, one for trust and one for usefulness. This decision was made based on previous research where the variables were combined to measure perception of AI (Araujo et al., 2020). However, for the additional analysis, the constructs will also be tested separately because the factor analysis showed they might be more effective on their own. They do differ indeed, with trust in AI being defined as having confidence and faith in algorithms and algorithm-driven decision-making (Shin et al., 2022, p.4). Usefulness of AI on the other hand focuses more on the extent to which a person believes that using a particular system would enhance their everyday interactions (Davis et al., 1989, 320). They will therefore also be tested separately in this supplementary analysis to find out whether people perceive AI differently for the separate constructs.

The item 'This AI improves the quality of the recommendations' originally belonged to the variable usefulness of AI, but the factor analysis showed that it belonged better in the trust in AI variable. Therefore, this item was added to this variable. Each hypothesis was tested again for these separate variables.

Effect of Knowledge of AI Privacy Implementations on Trust in AI and Usefulness of AI (H1)

A two-way MANOVA test was done to measure each hypothesis, with knowledge of AI privacy implementations and context of AI as independent variables and trust in AI and usefulness of AI as dependent variables. A Levene's test was done and the assumptions were met. A check for normality was done with measures of Skewness and Kurtosis was done as well, and these assumptions were also met because the values were between -3 and +3.

The results show that high knowledge (M = 4.86, SD = 1.03) and low knowledge (M = 4.86, M = 1.21) are very similar for the trust in AI variable. Because these results are almost the same, the difference is not significant F (1,127) = .01, p = .934, η^2 = .00. Therefore, H1 is rejected in this case.

The difference is slightly bigger for the usefulness of AI variable, where high knowledge (M = 5.69, SD = .91) is perceived to be a little less useful than low knowledge (M = 5.80, SD = .82). However, this difference is also too small to be significant, F (1,127) = .56, p = .457, η^2 = .00, meaning that H1 is also rejected here.

Moderating Effect of AI Context on the Relationship between Knowledge of AI Privacy Implementations and Trust in AI and Usefulness of AI (H2)

The moderation effect was also tested with the two-way MANOVA test, with both trust in AI and usefulness of AI as dependent variables. These results show that trust in AI is highest in the low knowledge, low stakes condition (M = 5.33, SD = .63). The second highest trust in AI takes place in the high knowledge, high stakes condition (M = 4.88, SD = 1.04). After this, trust in AI is highest in the high knowledge, low stakes condition (M = 4.85, SD = 1.03). Trust in AI is lowest in the low knowledge, high stakes condition (M = 4.42, SD = 1.44). The difference in trust in AI in these conditions is significant, F (1,127) = 6.10, p = .015, η^2 = .05, meaning that the second hypothesis is accepted in this case.

The results of the two-way MANOVA also show the numbers for the perceived usefulness of AI. Usefulness of AI is highest in the high knowledge, high stakes condition (M = 5.90, SD = .75). After this, the low knowledge and high stakes condition has the highest perceived usefulness (M = 5.87, SD = .84). The third highest condition is low knowledge, low stakes (M = 5.73, SD = .80). The least perceived usefulness of AI condition is high knowledge, low stakes (M = 5.48, SD = 1.01). The moderation effect for usefulness of AI is not significant, *F* (1,127) = .85, *p* = .360, η^2 = .01, so the second hypothesis is rejected here as well.

Effect of AI Context on Trust in AI and Usefulness of AI (H3)

The last hypothesis was also tested with the two-way MANOVA test, with both trust in AI and usefulness of AI as dependent variables. The results for this hypothesis show that trust in AI is higher in a low-stakes context (*M* = 5.08, *SD* = .89) than in a high-stakes context (*M* = 4.65, *SD* = 1.26). The difference in trust in AI in these contexts is significant, *F* (1,127) = 5.43, *p* = .021, η^2 = .04, meaning that in this case H3 is accepted.

Usefulness of AI is lower in a low-stakes context (*M* = 5.61, *SD* = .91) than in a high-stakes context (*M* = 5.88, *SD* = .79). This difference is not big enough to be significant, *F* (1,127) = 3.38, *p* = .068, η^2 = .03, meaning that H3 is rejected here.

An overview of the mean trust in AI and usefulness of AI can be seen in Table 4.1, Figure 4.2 and Figure 4.3 respectively.

Figure 4.2
Estimated marginal means of trust in AI across all four conditions

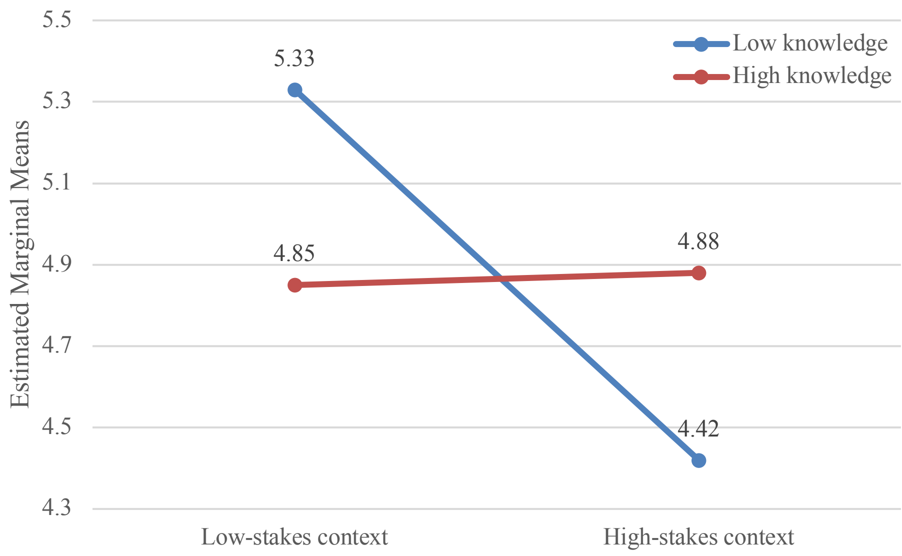
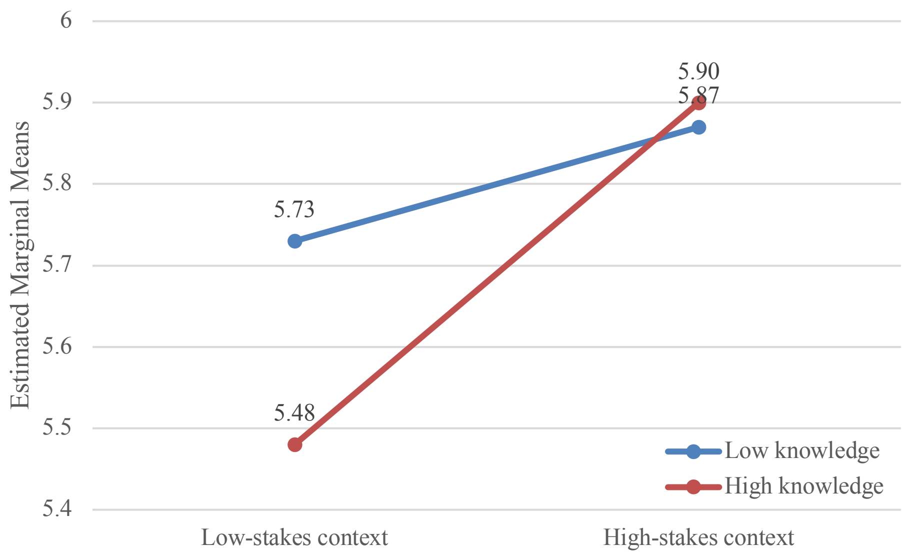


Figure 4.3

Estimated marginal means of usefulness of AI across all four conditions



5. Discussion

Even though the main results were not significant, they are still very interesting. It was anticipated that having more knowledge of what kind of personal information AI systems use would lead to a more positive perception of AI. The results are slightly contrary to this and showed that people who know a lot about how AI systems work perceive it somewhat more negatively than people who know less about how AI systems work. Furthermore, it was anticipated that AI privacy deployment in a lower-stakes context would lead to a more positive perception of AI than AI privacy deployment in a higher-stakes context. In the results, this effect can be seen because participants perceive AI systems somewhat better when it is used by Netflix to bring them movie recommendations than when it is used by doctors for a medical diagnosis. The interaction effect of knowledge and context shows an even more interesting effect because the results are contrary to each other when they are put together. When presented with information about how Netflix used their information, people perceived the AI systems much more positively when they had very little knowledge than when they had a lot of knowledge. In the higher-stakes medical diagnosis context, however, this effect was the opposite and having more knowledge resulted in a better perception of AI than when people had little knowledge. Perception of AI is the most positive when participants do not know how Netflix's AI systems work and most negative when participants do not know how doctors use AI systems to diagnose patients. The results of how useful knowledge can be in determining perception of AI are thus contradicting across the contexts.

Nevertheless, the extra analyses have shown that the results are not as clear-cut as they appear to be. The power analysis revealed weak power, and with a bigger sample, a stronger effect might have been noticed that would have been significant. Supplementary analyses were done because although the results were not significant, there was still an effect to be seen as previously explained. When we look at these results, where perception of AI was divided into trust in AI and usefulness of AI, significant results showed up. These show that trust in AI is significantly higher in the low-stakes context of Netflix recommendations versus the high-stakes context of medical diagnosis. Additionally, the interaction effect of knowledge and context had a significant effect on trust in AI. The results are still similar, where the highest trust in AI appears when people do not know a lot about AI systems in the Netflix context and trust in AI is lowest when participants have little information about AI systems in a medical diagnosis context. The main difference with perception of AI is that the mean differences were bigger in this case, which caused significant results. The other supplementary analyses, however, were still not significant.

Knowledge about AI Privacy Implementations does not Impact Perception of AI

Across all conditions and both the main analyses as well as the supplementary analysis, knowledge of AI privacy implementations appeared to be no significant indicator for perceived perception of AI. The results of this study are therefore not as expected and hypothesized, but they do still provide important information for certain theories. In an earlier part of this study, the algorithm aversion and algorithm appreciation theories were explained. These theories provide different reasons for why someone would be averse to or appreciate a system that uses an algorithm. Though each study regarding these theories found valid and reliable results, they are very contradictory as well. The results of this study portray exactly the same.

Reich and colleagues (2023) stated that presenting information about how an algorithm works only helps to get people to the same level of trust as decisions made by human forecasters and it is very hard to get beyond this. The non-significant findings prove that knowledge about how an AI system implements privacy rules does not increase people's perception of AI and does therefore not matter as a significant determinant. It is indeed shown to be difficult to improve people's perception of AI by giving them more information on how it works and what kind of information it uses. The results are thus quite complicated and should be viewed with care. Algorithm aversion is a very helpful theory to explain the results of this study, but it appears differently in each situation and has different determinants and effects.

Additionally, Logg et al. (2019) showed that expert forecasters were less keen on taking advice from algorithms, meaning that expertise, and thus knowledge about how algorithms or AI systems work would cause people's perception to decrease. The results of the current study are not significant and thus provide contradicting results for this statement. This information is useful because it shows that algorithm appreciation is not influenced by knowledge as much as was previously thought. However, even though the results are not significant, the difference can partially be found back in the results. In the low-stakes context, it is true that expertise and knowledge of AI privacy implementations decrease algorithm appreciation, but in a high-stakes context this cannot be applied. Only in a low-stakes context did more knowledge of the AI privacy implementations lead to a lower perception of AI. On the other hand, algorithm appreciation did take place for high knowledge in the high-stakes context, because perception of AI increased after participants were presented with more information about how the AI systems use their personal information.

This study has shown that knowledge does not have a significant influence on perception of AI and is therefore also not an important determinant of algorithm aversion or algorithm appreciation. People's aversion or appreciation towards AI does not increase or decrease based on the amount of information they receive. Many studies have found contradictory results on algorithm aversion and its determinants and more research should be done on this theory to find out the precise details of what the exact causes and consequences of this theory are. In the current study, the mean differences in the effect of knowledge of AI privacy implementations on perception of AI were only 0.05, which shows that it does not determine how positive people perceive AI to be. Even in the supplementary analyses, where perception of AI was split up into trust in AI and usefulness of AI, the mean differences were minimal. This suggests that even with additional testing, knowledge of AI privacy implementations does not have a significant impact on people's perception of AI. This information is contrary to what was found by previous studies and theories but still provides new insights and useful information (Araujo et al., 2020; Logg et al., 2019).

The Influence of the Context on Perception of AI

The third hypothesis explored the direct effect of the context in which an AI system is used on perception of AI. These results were also not found to be significant, meaning that the type of context did not influence people's perception of AI. These results can also be explained by multiple theories.

Based on the study by Dietvorst et al. (2015), which showed that mistakes by algorithmic forecasters are much more strongly accounted for than mistakes by human forecasters, it was thought that algorithm aversion would be stronger in a high-stakes context in which an AI system is used because the stakes of the information that is used in this context are higher. Thus, when mistakes are made by an algorithm or AI system in this case, the effects would be stronger and perception of AI was thought to be more negative in this case too. The results showed this to be partially true. Perception of AI was indeed more negative in the high-stakes context conditions versus the low-stakes context conditions, but this was only slightly more negative. The difference was not big enough to be significant. The difference is in line with the algorithm aversion theory, but the effect is not as strong as was thought and because the results are not significant, realistically they do not support the algorithm aversion theory because AI is perceived similarly for a high-stakes condition and a low-stakes condition. It does therefore not support the statement that algorithmic forecasters are much stronger accounted for than human forecasters in a high-stakes context.

The algorithmic appreciation theory is the opposite of the algorithm aversion theory and is about the fact that people are more likely to follow advice from algorithms than from humans. Similarly to algorithm aversion, the results of this study prove that knowledge of how the AI system implements privacy rules and the context in which it is used do not influence how much the AI systems are appreciated. Logg and colleagues (2019) showed with their study that people especially rely more on algorithmic advice for lower stakes tasks such as the prediction of the popularity of songs or romantic attraction. However, even though the results were not significantly different, the mean perceptions of AI are in line with this statement. People's mean perception of AI was more positive in a lower-stakes context than in a higher-stakes context. The difference was small but still noticeable. People thus appreciate AI systems slightly more positively in a lower-stakes context, which is in line with the algorithm appreciation theory.

Contextual integrity was defined by Nissenbaum (2004, p.155) as the fact that adequate privacy protection needs to be adjusted for the context, meaning that privacy protection matters should change according to the context in which they are being used. Connected to the privacy calculus theory, where people make calculations about the perceived benefits and costs of a certain situation, this theory focuses on whether the perceived benefits and costs are appropriate for the situation and whether enough privacy protection matters are taken. The stimulus materials that were presented in this study showed similar amounts of information being used to get to the end goal of either giving a movie recommendation or a medical diagnosis. Even though the nature of the information was different, the amount of personal information being used was the same and no mention of different privacy protection measures was mentioned. They showed no adjustment for the context, against the ideas of this theory.

The results showed no significant difference in perception of AI across the contexts. This is an important finding because even though privacy protection matters should be adjusted according to the context because some information is more important and should be better protected than others, it does not affect people's perception of AI when this is not accounted for. It is indeed still important that the regulations are followed for adequate privacy protection in different contexts, but the new insight that perception of AI does not change if this is not done is important information. It brings a new understanding of how contextual integrity is perceived and shows that people do not always view the importance of it as they maybe should.

The supplementary analysis where perception of AI was separated into trust in AI and usefulness of AI showed that the direct effect of context in which the AI system is used was significant for trust in AI. In the low-stakes context condition, trust in AI was more negative than in the high-stakes context condition. These findings are in line with the study by Filiz et al. (2023), which showed that people are more likely to trust decisions made by humans in a high-stakes context. Explained differently, it means that people are more likely to distrust AI systems in a high-stakes situation. This is exactly what the results of the supplementary analysis show.

In sum, even though the main analyses portrayed non-significant findings, they are still useful for explaining different theories. They bring new insight to the algorithm aversion and algorithm appreciation theories, as well as new findings for the contextual integrity theory which are not in line with the original theory but can still be very useful. The supplementary separated analysis of trust in AI and usefulness of AI further enhanced the understanding of the role that context plays in determining people's opinion of AI. When the variables are separated from each other, the effect of context becomes more clear and can be understood more thoroughly.

The Nuanced Moderation Effect

The second hypothesis focused on the importance of the moderation effect, and measured whether the context in which an AI system is used would influence the relationship between knowledge of AI privacy implementations and perception of AI. It was expected that the effect would become stronger in a context where lower-stakes personal information is used than in a context where higher-stakes personal information is used which would lead to more positive perceptions of AI in the lower-stakes context than in a higher-stakes context. However, as became clear from the results, the moderation effect is also not significant, meaning that the effect of knowledge of AI privacy implementations on perception of AI does not significantly differ depending on which context the AI system is used in. There are however differences to be seen, and these will be explained in the following paragraphs.

The results can be explained through the privacy calculus theory, which is about the calculation of privacy benefits and costs. When people decide to use something, they outweigh the perceived benefits against the perceived costs. Whether they decide to use something or not depends on their perception of it. Consequently, it is a part of the decision-making process of whether or not to use AI systems and products or services that utilise AI systems and is an important factor influencing people's perceptions. Willems et al. (2023) showed this phenomenon when they proved that the privacy calculus theory played a role in people's decision-making process of whether or not to use AI systems. The decision-making process of the privacy calculus theory can also be used to explain the results of the measured perception of AI in this study.

In this study, the low-stakes context was defined as a situation personal information is used for a less important purpose, in this case, movie preference on Netflix. Perception of AI was most positive when participants were presented with little knowledge about how their personal information was used in this context. Thus, for this condition, the trade-off between perceived benefits and costs regarding people's privacy was the best. In this condition, participants were at low risk because the information that was used by the AI system was only used to provide them with the best movie and series recommendations on Netflix, which comes with fewer risks than the other higher-stakes context. They were not made aware of the specific details of what kind of information was used from them. People could thus not make a clear well-informed decision on the perceived benefits and costs. However, because the context was considered to be low-stakes, likely they did not care about the type of information that was being used from them, leading to the perceived benefits and costs also being less important. The benefits were considered to be so high that the potential costs did not matter to them as much anymore. They did not know about them and also did not care about them, leading to the perceived perception of AI being the most positive in this condition.

Contrarily, when participants had more knowledge about Netflix's AI systems, their perception of AI was a lot more negative. It was the second lowest out of all four, only being 0.02 more positive than the most negatively perceived condition. Participants in this case were well-informed about what kind of personal information was used from them, which might have led them to believe that the costs were worse than if they had not known this. This can also be seen in the fact that little knowledge in this low-stakes context did lead to a better perception of AI. Even though the perceived benefits were the same, the perceived costs were higher when participants had more knowledge which led to a worse perception of AI.

In the higher-stakes context, where participants were presented with information about how AI systems are used to perform medical diagnoses, the influence of knowledge was the opposite. Here, having little knowledge about AI systems led to the most negative perception of AI. The mean difference with the most positively perceived condition was only 0.38, which was not statistically significant. However, it is still interesting to see how the calculation of benefits and costs differs in this situation because the perceived costs were higher. After all, the medical information that is used is of greater importance than information on which movie or series preferences someone has. The text in the stimulus materials presented to participants showed them that the AI systems can diagnose diseases with 98% accuracy, so it would make sense that the perceived benefits are also high because the AI system works very well. However, when participants had little knowledge about which personal information is used, their perception of AI decreased to the most negative out of all conditions. This means that in the higher-stakes medical diagnosis context, knowing more about AI systems was important for getting a better perception of AI.

This could also be seen in the fact that having more knowledge of the AI systems led to the second-best perception of AI. When participants are well-informed about what kind of information is used by the AI system, the perceived costs seem to decrease and the perceived benefits become more important, which could explain why the perception of AI increased for this condition. When participants know exactly what kind of information is used from them, they might consider the costs and thus the potential risks to be lower, which can lead to the calculation ending up with a more positive perception of AI.

Because the moderation analysis was close to significance, additional testing took place, which resulted in interesting insights. When the quickest speeder person was taken out of the sample, the moderation all of a sudden became significant, meaning that the previously described situations would indeed be true and that the context in which the AI system is used is a significant moderator variable in the relationship between knowledge of AI privacy implementations and perception of AI because the mean results of perception in AI differ big enough between the low-stakes context and high-stakes context. Furthermore, the moderation effect was also significant in the supplementary testing of the separate variable trust in AI, because the mean difference across the four conditions was big enough. This indicates that the context in which the AI system is used significantly moderates the relationship between knowledge of AI privacy implementations and perception of AI. The order in which trust in AI was highest was similar to perception of AI, with the only difference being that the trust in AI had got even better when participants had more knowledge in the Netflix situation, with it coming closer to the second highest instead of the lowest ranked condition. This effect is thus stronger than the same effect for perception in

AI. Additionally, it is important to note that trust in AI was generally perceived to be more negative than perception of AI across all conditions. This can partially be explained by the fact that the variable is separated, and it also makes the previously explained significant results more plausible. Trust in AI is different than general perception of AI, and people perceive different calculations of perceived benefits and costs. Because trust in AI resulted in lower means, the perceived costs were deemed stronger here and caused people to trust the AI systems less across all conditions compared to their general, slightly higher perception of AI.

6. Conclusion

The current study was one of the first to measure the combined effect of knowledge of AI privacy implementations and context in which the AI system is used on the perceptions of AI. Different factors can influence this perception, and this study set out to find to what extent knowledge of privacy implementations in AI and context in which the AI system is used affect people's perception of AI. This was done with an experiment where participants were presented with one of the four different stimulus materials in which different amounts of knowledge (low and high) about privacy implementations in two different contexts (low-stakes and high-stakes) were presented to the participants. They were then asked about their perception of AI according to the text they had previously read.

Based on previous studies, it was thought that more knowledge of privacy implementations in AI would lead to a more positive perception of AI. Additionally, the context in which the AI system was used was thought to influence this relationship, where AI systems which were used in a low-stakes context were thought to have a stronger impact on the relationship between knowledge of AI privacy implementations and perception of AI than AI systems used in a high-stakes context. Furthermore, AI privacy deployment in a low-stakes context was thought to lead to a more positive perception of AI than in a high-stakes context.

The results from the collected data of the final dataset showed no support for all three predicted hypotheses. Thus, the answer to the research question is that the amount of knowledge of privacy implementations in AI does not have a significant effect on people's perception of AI and that this effect does not differ between the importance of the context. Perception of AI does not become significantly more positive after someone has more knowledge of how the AI systems handle people's personal information. Furthermore, the context in which an AI system is used does also not significantly change people's perception. The two variables knowledge and context together also do not significantly influence people's perception of AI. In clear terms, this means that with the current results, knowledge about AI privacy implementations and the context in which an AI system is used are not significant determinants of perception of AI.

However, as became clear from the multiple extra tests that were done with the final dataset, the results were easily influenceable and not as clear-cut as they appeared to be. The moderation effect was very close to significance, and when the quickest speeder was accounted for this effect was indeed significant. Moreover, when perception of AI was separated into trust in AI and usefulness of AI, the direct effect of context and the moderation effect were significant. Accordingly, this means that these might in fact be significant determinants of the variable trust in AI. Additionally, the power analysis revealed that with a bigger sample, the power of the study would be improved, which might help to detect stronger effects.

The results of this study were not significant and any link to existing theories should be taken with caution. Even though a possible explanation for them is given, the differences in mean perceived perception of AI across the conditions were very small. However, it is important to note that participants were presented with fictional stimulus materials. In real-life scenarios with information that is better adapted to the situation and closer to people's experiences, the mean differences could be more pronounced. Thus, the effect may still be there and can be explained according to the current results. Nevertheless, it should be kept in mind that perception of AI across all conditions was very similar for the current conditions that were studied in this thesis. This is an important observation as well and can help to potentially further explain how the amount of knowledge of AI privacy implementations and the context in which an AI system is used have little effect on perception of AI. Practical and theoretical implications for these results will be discussed and limitations and strengths of this research as well as suggestions for future research will be given.

Practical and Theoretical Implications

The findings of this study are important for people who are working with AI. Because AI systems are constantly improving and changing, they are being implemented in more aspects of society and being used in many different contexts. The two examples from the stimulus materials, entertainment and health, are just a start. It was therefore important to find out how perception of AI is influenced, and whether knowledge of its privacy implementations and the context in which it is applied affect the perception. The results are not significant, but still very valuable and have important practical implications. They show that the amount of knowledge that is given about how the AI system deals with people's personal information and the context in which the AI system operates do not have a significant impact on perception of AI. This is important information for marketeers and business representatives who are trying to influence people's perception of AI regarding their services. The results showed that they do not need to change the amount of knowledge or explanation of the context in which the AI system is used. Nevertheless, the small difference that could be seen in the mean perception of AI across the conditions is an indication that it might still have a small impact. It shows that in a high-stakes context, such as the medical diagnosis that was used in this study, it is important to be transparent about what kind of information is used. In a low-stakes context, such as the Netflix recommendations, this is not considered to be as important, because perception was higher when people were not very well-informed about the AI systems. The end goal in this case is more important than what is used to get there. The results of this study can still be used by companies, but for optimal results, they should be studied within the specific context in which they will be used. If this is done and the optimal combination is achieved, with the best amount of knowledge that can be given to someone in a certain context, perception of AI will be highest and people will be more likely to accept working with the AI system. If the best condition is not achieved, it might work counteractive and decrease perception of AI. The results of this study are thus a good guideline to find out the best condition that is needed to get to the most positive perception of AI possible. Recommender systems are already a very profitable aspect of Netflix's business model, but this information could help to improve it even more (Azaria et al., 2013, p.121; Manchanda, 2021). With this information, businesses who are trying to improve their clients' perception of AI could try out the determinants for their situation, to find out whether the results of the current study get stronger when they are applied to real-life cases. They could stay better informed of potential trends and include experiences that are better tailored to their client's needs and wants (Houston, 2024).

The theoretical implications of this study include a new perspective on perception of AI and its determinants. The direct effect of amount of knowledge of AI privacy implementations on perception of AI had not been studied before. Similarly, the effect of context in which the AI systems are used on perception of AI and the combination of knowledge and context as the moderation effect on perception of AI were also new. There can be many different determinants of perception of AI, and as the innovations keep changing and improving, they will likely change as well. It is therefore important that existing theories are constantly updated with new views and results, which is exactly what this study has done. It has added a new perspective on existing theories such as algorithm appreciation, algorithm aversion and the privacy calculus theory. Previously, it was already known that different determinants can result in different perceptions, and thus influence algorithm appreciation and algorithm aversion (Araujo et al., 2020, p.613; Hou & Jung, 2021, p.1). This study has shed new light on the determinants of knowledge and context and shown that even though they do matter slightly, they do not severely impact perception of AI and thus whether people will appreciate or be averse to AI systems. Furthermore, the privacy calculus theory and contextual integrity theory have shown that in each context, the personal information used by AI systems has to be adjusted to the rules of the certain context leading to different considerations for the costs and benefits (Nissenbaum, 2004, p.155; Willems et al., 2023, p.2128). This effect was shown in the moderation analyses, where little knowledge of AI privacy implementations worked well in the low-stakes context but did not work very well in the high-stakes context where it caused perception of AI to be more negative. The perceived calculation of perception is thus adjusted for these variables and influenced by them. All of these insights can be used for further research on this topic, and help to better understand how people view AI and the factors that impact this.

Limitations, Strengths and Future Research

This study is a Master's thesis, and even though it was set out to be as good as possible, there are still some limitations and points of improvement. Because of the relevant topic and interesting but non-significant results, recommendations for future research will be made to improve further research on this topic.

Firstly, the stimulus materials were designed to be as similar to each other as possible. Four different stimulus materials were created to combine both the independent variable knowledge of AI privacy implementations and the moderator variable context in which the AI system is used. They were of equal length and included similar features such as additional information in the low knowledge conditions and a detailed listing of personal information used in the high knowledge conditions. A limitation regarding this subject however was that there was a lot that had to be accounted for in the stimulus materials and even though they were designed to be as similar to each other as possible there might still have been too many differences. If the focus was only on the difference in knowledge, the stimulus materials might have been more similar and it would have been more clear that people's perceptions differed because of what they saw in the condition presented to them. Right now, the difference between the four conditions might have been too big, making it harder to measure exactly what was intended to be measured. Furthermore, only two categories were used for both variables, low and high knowledge and low- and high-stakes context. This decision was made to keep it manageable for this study because there was limited time and resources. There are however many different types of knowledge people can have and many different contexts in which AI systems can be used. Future research should therefore focus on creating stimulus materials that more clearly depict the specific details of what they are researching so that the results are better comparable and should include different settings to see whether the results change.

Next, the participants for the survey were gathered through convenience sampling. Because of the time constraint, this was the best option to gather the necessary amount of data in a small amount of time. It was indeed proven to be a successful method to gather the needed amount of participants within the given time frame. However, this might have caused the sample to be a little too similar. Most participants (71.8%) resided in the Netherlands and 61% of the sample fell in the age range of 22-25. There were outliers and other demographics included as well, but a big part of the sample was very similar. This might have influenced the results. Because of the limited time, it was still the best option for this study, but future studies with more time should try to get an even more diverse sample so that the results are better applicable to the general population.

Additionally, the study was done through an online experiment. This was an easily accessible way for participants to participate in the study and to gather responses from many different places. It also came with risks however such as less control over the participants. They were not being watched while taking part in the experiment and it was therefore not completely sure whether they paid attention to every single question. Precautions were taken to combat this as much as possible, such as the use of an attention check and a manipulation check. However, some participants still had to be deleted because their answers were suspicious. Future research should therefore consider the option of real-life experiments or surveillance equipment to watch participants more closely while they participate in the study to make sure that their answers are completely reliable.

Lastly, previous knowledge of AI might have been a limitation in this study because the stimulus materials did not apply the same to everyone because of it. Even though previous knowledge was measured and evenly distributed across the conditions, it might have had a bigger impact than what could be seen in this study. For the current study, it did not matter as much because the randomisation check showed that all levels were evenly distributed across the conditions, but as AI becomes even more important in our society and personal lives, people's knowledge will also vary a lot more than the seven points that were currently on the scale. Furthermore, participants were asked to rank their own knowledge and it was not measured with questions that specifically tested their knowledge. To improve future studies on this subject, this should be accounted for, for example by measuring it more thoroughly or excluding participants who have too much knowledge to make sure that the stimulus materials have the same effect on everyone.

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Appendix

Appendix A: Qualtrics Survey

Survey Flow

Block: Informed consent (2 Questions)
Standard: Participant's Previous Knowledge of AI (2 Questions)

BlockRandomizer: 1 - Evenly Present Elements

- **Standard: Condition 1 (high knowledge, low stakes) (3 Questions)**
- **Standard: Condition 2 (low knowledge, low stakes) (3 Questions)**
- **Standard: Condition 3 (high knowledge, high stakes) (3 Questions)**
- **Standard: Condition 4 (low knowledge, low stakes) (3 Questions)**

Standard: Dependent Variable Measurements (2 Questions)
Standard: Attention Check (1 Question)
Standard: Manipulation Check (3 Questions)
Standard: Demographics (5 Questions)
Standard: Debriefing (2 Questions)

Page Break

Start of Block: Informed consent

Q1 Dear participant,

Thank you for your interest in this research. In this study you will be provided with some information about Artificial Intelligence (AI), after which you will be asked questions about your perception of AI. The purpose of this study is to investigate which factors have an effect on your perception. Please answer each question carefully and truthfully, I am sincerely interested in your personal opinion. There are no right or wrong answers.

Confidentiality of data
All research data remains completely confidential and is collected anonymously. You will not be identifiable. There are no foreseeable risks or discomforts associated with participating in this research.

Voluntary
If you now decide not to participate in this research, this will not affect you. If you decide to cease your cooperation during the survey, this will in no way affect you either. You can cease your cooperation without giving reasons.

Time involvement
Your participation in this study will take approximately 5-10 minutes. You may interrupt your participation at any time.

Payments
There will be no monetary compensation for your participation.

Further information
If you have questions about this research, in advance or afterwards, you can contact the responsible researcher, Lotte Vianen, email: 703386lv@student.eur.nl. If you want to invoke your rights or if you have a question concerning privacy about this study, you can contact Erasmus University's DPO (Data Protection Officer) at fg@eur.nl.

I hope to have provided you with sufficient information. I would like to take this opportunity to thank you in advance for your assistance with this research, which I greatly appreciate.

Kind regards,
Lotte Vianen

Informed consent If you understand the information above and freely consent to participate in this study, click on the 'I agree' button below to start the questionnaire.

- o I agree (1)
- o I do not agree (2)

Skip To: End of Survey If If you understand the information above and freely consent to participate in this study, click on... = I do not agree

End of Block: Informed consent

Start of Block: Participant's Previous Knowledge of AI

Previous knowledge Before we start with the survey I would like to ask you about your knowledge of AI. Please fill in the following question:

Previous knowledge 1 How would you rate your knowledge of AI?
- o Very good (1)
- o Good (2)
- o Average (3)
- o Poor (4)
- o Very poor (5)
- o No knowledge (6)
- o I don't know (7)

End of Block: Participant's Previous Knowledge of AI

Start of Block: Condition 1 (high knowledge, low stakes)

Q3 You will now read a text which explains how Netflix uses AI. Please read it carefully. After 30 seconds you will be able to continue to the next page.

Q22 **AI use by Netflix**
Artificial intelligence (AI) can be used in many aspects of daily life. An example of this is the recommendations of films and series on Netflix. When you use Netflix, multiple information points about you are collected and used to create a personal home page that best fits your interests. The company does this to make it as easy as possible for you to find a good film or series that it thinks you would like. It uses a type of artificial intelligence, called a machine learning algorithm, specifically a recommender system. This system uses your personal information to find the best recommendations for you. It includes information such as:
- Your age
- Your gender
- Your location
- At what time you are watching
- Your personal viewing history

Netflix only uses your private information to provide you with the best recommendations on the platform, they are not used by anything or anyone else. You can always opt-out or change the amount of information being used.

Q18 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: Condition 1 (high knowledge, low stakes)

Start of Block: Condition 2 (low knowledge, low stakes)

Q4 You will now read a text which explains how Netflix uses AI. Please read it carefully. After 30 seconds you will be able to continue to the next page.

Q23 **AI use by Netflix**
Artificial intelligence (AI) can be used in many aspects of daily life. An example of this is the recommendations on Netflix's homepage. Netflix is an online streaming platform where you can watch films and series. There are millions of titles available on the platform, which means that there is always something that you might like. However, it can be hard to go through every single title by yourself to find one that fits your interests. To overcome this problem, the company uses a type of artificial intelligence to provide you with recommendations for what it thinks you would like to see. This means that when you use Netflix, personal information is collected and used to create a personal home page that best fits your interests and create the best experience for you. With the help of this tool, the company is able to provide you with a better service and make your viewing experience easier and more enjoyable.

Q19 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: Condition 2 (low knowledge, low stakes)

Start of Block: Condition 3 (high knowledge, high stakes)

Q5 You will now read a text which explains how doctors can use AI. Please read it carefully. After 30 seconds you will be able to continue to the next page.

Q32 **AI use by doctors**
Artificial intelligence (AI) can be used in many aspects of daily life. An example of this is to diagnose diseases and medical conditions. Recent advancements in AI techniques have led to remarkable improvements, enabling the diagnosis of multiple diseases such as

Alzheimer's and cancer with 98% accuracy. They do this by analysing images from a CT scan or MRI with machine learning and deep learning models to diagnose the disease. With the help of AI, patients can be diagnosed faster which helps with faster treatment. Certain personal information about you will be collected and used by the AI system to get the right diagnosis. This includes information such as:

- Your age
- Your gender
- Your location
- Your symptoms
- Your previous medical history

Medical AI systems only use your private information to provide you with the best diagnosis, they are not used by anything or anyone else. You can always opt-out or change the amount of information being used.

Q20 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: Condition 3 (high knowledge, high stakes)

Start of Block: Condition 4 (low knowledge, low stakes)

Q6 You will now read a text which explains how doctors can use AI. Please read it carefully. After 30 seconds you will be able to continue to the next page.

Q25 **AI use by doctors**
Artificial intelligence (AI) can be used in many aspects of daily life. An example of this is to diagnose diseases and medical conditions. Traditionally, when you are ill you can go to a doctor to help you get better. The doctor looks at your symptoms and makes a diagnosis, after which you will be treated for it. Recent advancements in AI techniques have led to remarkable improvements, enabling the diagnosis of multiple diseases such as Alzheimer's, cancer, diabetes, heart disease and many more, with 98% accuracy. The AI systems look at your symptoms and use your personal information to make the correct diagnosis for you and recommend the best treatment. Previously, the whole process took long because doctors had to carefully examine everything before they could make a diagnosis. With the help of AI, patients can be diagnosed and treated faster. The process saves time and helps to ease the workload for doctors.

Q21 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: Condition 4 (low knowledge, low stakes)

Start of Block: Dependent Variable Measurements

Trust in AI I would now like to measure your perception of AI. Please answer to what extent you agree with the following options.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I trust the recommendations by this AI platform. (1)	○	○	○	○	○	○	○
Recommended results via this AI process are credible. (2)	○	○	○	○	○	○	○
These AI personalized results are dependable and trustworthy. (3)	○	○	○	○	○	○	○

Usefulness of AI

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Using this AI saves time. (1)	○	○	○	○	○	○	○
Using this AI improves efficiency. (2)	○	○	○	○	○	○	○
This AI is useful. (3)	○	○	○	○	○	○	○
This AI increases productivity. (4)	○	○	○	○	○	○	○
This AI improves the quality of the recommendations. (5)	○	○	○	○	○	○	○

End of Block: Dependent Variable Measurements

Start of Block: Attention Check

Attention Check To check if you are still paying attention, please answer 'Agree' to this question.

- o Strongly disagree (1)
- o Disagree (2)
- o Neither agree nor disagree (3)
- o Agree (4)
- o Strongly agree (5)

End of Block: Attention Check

Start of Block: Manipulation Check

Q26 Please answer the following questions about the information you just read about how AI can be used.

Manipulation Check 1 In the text that you read, in which context was AI used?

- o Netflix recommendations (1)
- o Medical diagnosis (2)
- o Spotify music recommendation (3)
- o Other (please specify) (4)
  ____
- o I don't remember (5)

Manipulation Check 2 Based on the text you read, to what extent do you know that AI systems make recommendations using ...

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
your age. (1)	o	o	o	o	o	o	o
your gender. (2)	o	o	o	o	o	o	o
your location. (3)	o	o	o	o	o	o	o
And give you the ability to opt out of your information being used. (4)	o	o	o	o	o	o	o

End of Block: Manipulation Check

Start of Block: Demographics

Q10 Now I would like to gather some information about you.

Gender What is your gender?

- o Male (1)
- o Female (2)
- o Other (3)

- o Prefer not to say (4)

Age How old are you? (in years)

____

Education What is the highest form of education you have completed?

- o Primary school (1)
- o High school (2)
- o MBO (secondary vocational education) (3)
- o HBO (university of applied sciences) (4)
- o University bachelor (5)
- o University master (6)
- o Other (please specify) (7) ____

X→

Q1 In which country do you currently reside?

▼ Afghanistan (1) ... Zimbabwe (1357)

End of Block: Demographics

Start of Block: Debriefing

Q14 Thank you very much for participating in this study!

IMPORTANT: Please make sure to click the box at the end of this page to save your results.

This experiment was about the perception of AI. In four different conditions, I tried to measure whether amount of knowledge and context in which AI is used have an effect on what you think of AI. You were randomly assigned to one of the four conditions:

- High knowledge in the context of Netflix's recommender system
- Low knowledge in the context of Netflix's recommender system
- High knowledge in the context of medical diagnosis image recognition
- Low knowledge in the context of medical diagnosis image recognition

The information you saw was based on real life but adapted to fit the study better. You can read more about the use of AI in these contexts here:

Kumar, Y., Koul, A., Singla, R., & Ijaz, M. F. (2022). Artificial intelligence in disease

diagnosis: A systematic literature review, synthesizing framework and future research agenda. Journal of Ambient Intelligence and Humanized Computing, 14, 8459-8486. https://doi.org/10.1007/s12652-021-03612-z

Netflix. (n.d.). How Netflix's recommendations system works. Netflix Help Center. https://help.netflix.com/en/node/100639

The information you provided is solely for this experiment and will not be shared with any third party.

To finish, please click the box below and click next to save your answers.

Debriefing

○ By clicking this box, I agree with my participation in this study and I agree to submit my data for analysis. For more information about the research, you are welcome to contact Lotte Vianen at 703386lv@student.eur.nl. (1)

End of Block: Debriefing