CATCH ME IF YOU SCAN

A QUANTITATIVE STUDY ON CUSTOMERS' PSYCHOLOGICAL AND BEHAVIORAL RESPONSE TO AI-ASSISTED SURVEILLANCE IN SELF-CHECKOUTS

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Catch me if you scan: A quantitative study on customers' psychological and behavioral response to AI-assisted surveillance in self-checkouts.

Abstract:

Artificial Intelligence is on everyone's lips ever since ChatGPT was released in November 2022, and AI is being integrated into more technological solutions by each passing day. The purpose of this thesis is to investigate how the behavioral intentions of customers of Swedish grocery stores change when exposed to different degrees of AI-assisted surveillance in their self-checkout experience. An online survey was used to collect 743 responses where the main theory for the analysis was the S-O-R model which is examined with a Structural Equation Modeling (SEM) approach. The results showed no significant change in behavioral intentions, but other significant effects on emotions and perceptions and the mediating effect of those variables are discussed. The relevance of being watched and the importance of how one discloses information is speculated to play a role in the experience.

Keywords:

Artificial Intelligence, Grocery Stores, Self-checkouts, Surveillance, Trust, Privacy concern, Intrusiveness, Vulnerability, Word of mouth, Revisit intention, Intention to use.

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1. Introduction

Can a single artificial intelligence (AI) program save grocers around the world millions of dollars by preventing theft? Artificial Intelligence has been covered and adopted by the general public ever since OpenAI released an early demo of ChatGPT on November 30, 2022 (Marr, 2023a). The number of solutions being assisted by artificial intelligence is increasing and are being integrated into our daily lives more and more. As the integration of artificial intelligence increases, so does the need to understand what effects this technological boom has on consumers' perceptions of daily activities such as chatting with a support agent, interaction in the workplace, and even when shopping for groceries. The importance of being informed and aware becomes important to assimilate to the unknown that is our current technological future.

Meanwhile, theft in grocery stores has increased since the introduction of the self-checkout and grocers in Sweden are desperate to find a solution to the problem (Norman, 2023). Grocers in the U.S. have amongst other solutions turned to AI enabled self-checkout systems which are supposed to be effective against deviant behavior (Silverstein, 2020). The purpose of this thesis is therefore to investigate what effects a possible integration of artificial intelligence into the self-checkouts of grocery stores has, and how it is received by the Swedish customers.

1.1. Background

This section aims to provide a background of firstly grocery stores in Sweden. Secondly, self-checkouts which is the alternative to traditional checkouts. Thirdly, an overview of theft in grocery stores and lastly, a short overview of different artificial intelligence solutions used in grocery stores today.

1.1.1. Grocery stores in Sweden

In Sweden, the grocery store sector is characterized by a rich history and a diverse market landscape. The three biggest actors in Sweden are ICA, Axfood and Coop, who in 2022 retained respective market shares: 50.3%, 20.5%, 17.5% (Delfi, 2023). According to Axfood (2022), the Swedish food retail market segments can be divided into three categories: discount, hypermarkets, and traditional grocery. ICA and Coop are mainly focused on the hypermarkets and traditional grocery, whereas actors such as Axfood can be found playing in all three market segments (Axfood, 2022).

1.1.2. Self-checkouts

The first self-checkout machine was introduced in 1986 by the North American company Kroger (Meyersohn, 2022). According to the Cambridge Dictionary (2024), a

self-checkout is a system of customers in a store using a machine to add up the prices and pay for goods they have bought. Coop introduced their first self-checkouts (SE: snabbkassor) in 2008 (Coop, 2008). Where the idea was for people to be able to make complimentary shopping, rather than large shopping. This means that the self-checkouts were meant to be used for people who shopped a smaller quantity of items.

1.1.3. Theft in grocery stores

In Sweden there have been complaints from retailers that the self-checkout systems are enabling theft (Svensson, 2023a). This has even led to certain retailers closing their self-checkout areas to stop the theft (Svensson, 2023a). In the rest of the world the problem is the same with research in North America showing that nearly one in seven shoppers have intentionally stolen from self-checkout (Reuter, 2023). According to Michael Johansson, store owner, their losses of two million SEK a year decreased rapidly when they closed their self-checkouts (Svensson, 2023a). One of the ways theft occurs is to not scan an item, another example is entering the code for a cheaper item instead of the actual item (Reuter, 2023).

1.1.4. Artificial intelligence

According to Google Trends (n.d.), search volume for "Artificial Intelligence" rose from medium popularity in November 2022 to peak popularity in May 2023. Copeland (2024) states in Britannica that Artificial Intelligence is the ability of a computer or computer-controlled robot to perform tasks that are commonly associated with the intellectual processes characteristic of humans, such as the ability to reason. They also write that there are no AIs that match full human flexibility, however, there are certain instances of AIs performing specific tasks as well as humans (Copeland, 2024). Instances where Artificial Intelligence have progressed in its applications are: healthcare, customer service, finance, manufacturing, transportation, agriculture, retail and more (Marr, 2023b).

1.1.5. Artificial intelligence solutions in grocery stores

In Sweden, the predominant choice of action currently to prevent theft are either closing the self-checkouts, introducing an age limit of 18 years of age, having randomized controls, or a mixture of the latter two (Svensson, 2023b). In other countries, grocery stores have started to implement Artificial Intelligence technology to prevent shoplifting. In North America, major retailers are trying anti-theft solutions such as facial-recognition cameras, image recognition software, autonomous security robots, radio-frequency identification tags (RFID) and smart case locks (Woods, 2023). Some of these technologies have been around for years but are now superpowered by AI. Technology companies are developing AI solutions that can be integrated with existing technologies like security cameras and self-checkouts (Woods, 2023). For example, the

American grocery chain Kroger signed a deal with Irish artificial intelligence firm Everseen (Silverstein, 2020). The Visual AI™ system (Everseen, n.d.) uses Artificial Intelligence to recognize deviant consumer behaviors and alert employees to prevent shoplifting. In Australia, the grocery chain Woolworth installed an AI-technology which detects and alerts suspected theft in self-checkouts through overhead security cameras (Taylor, 2023). Woolworth received criticism from Digital Rights Watch for treating every customer as a suspect and normalizing everyday surveillance with invasive technologies (Taylor, 2023). In England, an increasing number of supermarkets are adopting a facial recognition technology called Facewatch to stop shoplifting (Satariano & Hill, 2023). The technology alerts security guards when an individual with shoplifting history enters the store, creating a form of shoplift watchlist (Satariano & Hill, 2023). The chain Southern Co-op has received criticism from the Privacy Rights Group for only implementing Facewatch in stores located in poor areas, which is discriminating to poor people (Das, 2024). Another solution is unmanned stores enabled by AI, where Amazon Go is perhaps the most well-known example. Amazon Go applies their "Just walk out technology" (JWO), which includes AI powered technologies like sensor fusion, cameras with computer vision, and RFID tags (Amazon, 2024). The JWO technology allows shoppers to enter a store, pick up items and just walk out without having to wait in a checkout line or stop at a cashier (Amazon, 2024). The European Data Protection Supervisor criticized the JWO technology for normalizing constant surveillance by tracking and monitoring shoppers every move with AI which can create a feeling of being under constant surveillance (Enescu, 2024). Furthermore, they criticized the lack of transparency regarding collection and use of personal data (Enescu, 2024). Even if AI solutions in grocery stores have great potential to prevent theft and make shopping more efficient, the question remains whether legislators and customers will approve of the increased surveillance in everyday life.

1.2. Purpose and research questions

1.2.1. Purpose

The purpose of this thesis is to analyze how customers respond to surveillance assisted by artificial intelligence integrated into self-checkouts in Swedish grocery stores. Using a quantitative method, different degrees of artificial intelligence surveillance was designed through using an online survey containing different scenarios with questions. We hope to provide practical insights into customers' response to artificial intelligence in grocery stores. The thesis follows a deductive approach as the findings will be discussed based on the empirics in the domain of Stimulus-Organism-Response Model and supporting theories.

1.2.2. Research questions

How do customers respond to different degrees of AI-assisted surveillance in grocery store self-checkouts?

More specifically;

- *Which perceptions and emotions help explain their behavioral intentions?*
- *Does information disclosure make a difference in how they respond?*

1.3. Delimitations

Firstly, the study was limited to the Swedish market since the implementation of Artificial intelligence in grocery stores is a rather new phenomenon in Sweden. In addition, legal regulations of Artificial Intelligence differ between countries. On March 13th 2024, EU approved the Artificial Intelligence Act which purpose is to protect fundamental rights and democracy by banning certain AI-applications based on its perceived risk on society (European Parliament, 2024). Some of the banned AI applications in EU include biometric categorization systems, facial recognition databases based on CCTV footage, social scoring and predictive policing (European Parliament, 2024).

Secondly, the study was limited to AI-assisted surveillance in self-checkouts. When selecting an AI-solution for this study, several criteria had to be met. The AI-technology had to be (1) legal in Sweden, (2) effective against theft and (3) easy to integrate with existing security cameras or self-checkouts to keep investments down for grocers. With these criteria in mind, we compared different AI-solutions and identified one with great potential to reduce shoplifting in Swedish grocery stores in the future. The selected technology has capabilities within aisle theft detection and employee monitoring, but this study is solely focusing on AI-assisted surveillance in self-checkouts.

Thirdly, the study was conducted online and not in a physical store. To the best of our knowledge, the selected AI-solution does not exist in Swedish grocery stores yet which made it impossible to conduct the experiment in a grocery store. Therefore, an online survey with scenarios was distributed.

1.4. Expected contributions

We hope to produce valuable insights for Swedish grocery stores who are on the fence regarding getting rid of self-checkouts or investing in AI-solutions to mitigate deviant customer behaviors. AI-solutions are effective against theft, but the question remains whether customers will approve of the increased surveillance.

Further we aim to investigate the importance of transparency by companies who use AI-technologies. Does information disclosure regarding theft prevention affect how customers respond? If so, information disclosure could be used as a communicative tool to make customers feel more comfortable with AI-assisted surveillance.

Lastly, previous research on self-checkouts and AI in grocery stores are primarily focused on technology acceptance theories that measure customers' evaluation of technological attributes, attitudes, and intention to use the technology (TAM, UTAUT, HISAM, Attitudinal model, Attribute based model). However, the added element of being confronted with AI-assisted surveillance in the self-checkout might evoke feelings and behaviors that previous studies had no reason to test. By modifying the Stimulus-Organism-Response model by Mehrabian & Russell (1974) and applying it to a new setting, we hope to provide a theoretical framework that helps explain customers' internal and external response to being confronted with surveillance technology.

2. Literature review & theoretical framework

In the following chapter, a literature review of previous research is provided. From this review, multiple research gaps are identified. This is followed by an outline of the theoretical framework and the development of hypotheses. The chapter concludes with the presentation of a conceptual model.

2.1. Literature review

2.1.1. Customers' response to self-service technologies

Since the introduction of the self-checkout machine in 1986 (Meyersohn, 2022), researchers have been trying to understand what implications self-checkouts and other related self-service technologies (SST) have on businesses and their customers. Dabholkar (1994) conducted early research on self-service technologies and developed the Attitudinal Model for technology-based self-service by extending the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975) with three expectancy values (ease of use, performance, fun) that influence attitude to use, intention to use and actual use. Dabholkar & Bagozzi (2002) later applied the Attitudinal Model to explore consumers' attitudes to touch screen ordering versus ordering by human employees in a fast-food restaurant. The results supported that all three expectancy values (ease of use, performance and fun) had positive effects on attitude towards using the touch screen which had positive effects on intention to use. The situational factor perceived waiting time and the consumer traits novelty seeking and self-consciousness had a moderating effect on the relationship between attitude and intention (Dabholkar & Bagozzi, 2002).

Dabholkar (1996) also developed the Attribute Based Model and the Overall Affect Model where cognitive evaluations of technological attributes (speed of delivery, expected ease of use, reliability, enjoyment and control) and affective evaluations (attitude toward using and need for interaction with service employee) influence the expected service quality of technology-based self-service which influence intention to use. Dabholkar et al. (2003) applied the Attribute Based Model in a research paper on consumers' reasons for using or avoiding self-scanning technology in stores. The result showed that consumers who prefer to interact with employees and find self-scanners difficult to use tend to avoid self-scanning, while consumers who did not prefer to interact with employees appreciated the self-scanning which increased their usage intention. It was also found that the situational factors store crowding and number of items being purchased had an impact on the intention to use the self-scanning (Dabholkar et al., 2003).

Another theoretical model that has been frequently applied in studies about customers' attitude towards self-service technology is the Technology Acceptance Model (TAM)

by Davis et al. (1989). TAM is also a development of TRA and explains how perceived usefulness and perceived ease of use influence users' attitude towards using the technology, intention to use and actual use (Davis et al., 1989). Weijters et al. (2007) applied TAM in a research paper about customers' use of self-scanning in retail. In addition to the variables in TAM, the authors added perceived reliability and perceived fun as antecedents to attitude. The results showed that all four antecedents had a significant effect on attitude towards using self-scanning, where perceived usefulness had the highest explanatory power. It was also confirmed that customers' attitude has a significant impact on actual self-scanning usage. In addition, the results showed that education and gender affected how important customers believe certain features of self-scanners are (Weijters et al., 2007).

The Technology Readiness Index (TRI) by Parasuraman (2000) is another frequently used theory within this research field. TRI consists of four dimensions of individuals' feelings about the technology which influence their technology readiness. The four dimensions are divided into two contributors (optimism and innovativeness) and two inhibitors (discomfort and insecurity) (Parasuraman, 2000). In 2007, a combination of TAM and TRI called the Technology Readiness and Acceptance Model (TRAM) was introduced (C.-H. Lin et al., 2007). Elliott et al. (2012) applied the TRAM model in a study about self-scanning to explore whether technology readiness had an impact on attitude towards using self-scanning. The study confirmed that the four self-scanning attributes perceived usefulness, perceived ease of use, perceived reliability and perceived fun have a direct effect on consumers' attitude. The results also confirmed that technology readiness has a significant impact on all four attributes (Elliott et al., 2012).

The SSTQUAL scale was developed by J.-S. C. Lin & Hsieh (2011) to assess the service quality of self-service technology encounters. The scale has seven dimensions (functionality, enjoyment, security, assurance, design, convenience and customization) that determine the overall service quality of self-service technology which influence customers’ behavioral intention (J.-S. C. Lin & Hsieh, 2011). Demirci Orel & Kara (2014) applied the SSTQUAL scale in a study about self-checkouts in supermarkets. The result showed that the perceived service quality of self-checkouts has a positive influence on loyalty through customer satisfaction. The study also found that younger customers have higher tendencies to use self-checkouts in supermarkets (Demirci Orel & Kara, 2014). Fernandes & Pedroso (2017) conducted a similar study where they applied the SSTQUAL scale and the Attribute Based Model to explore the effect of self-checkout quality on customer satisfaction and repatronage in a retail context. They found that customers' age and frequency of using self-checkouts have an impact on how important they perceive certain attributes. Young customers perceive a higher sense of control over the technology and customers who use self-checkouts more frequently perceive it as fun and easy to use. The results also showed that service quality

influences overall satisfaction which has a positive impact on repatronage intentions towards the store (Fernandes & Pedroso, 2017).

Multiple studies on self-service technology have found that technology anxiety, age and gender affect usage intentions. Meuter et al. (2003) conducted a study to explore how technology anxiety influences consumers' usage and experiences with self-service technologies. The study found that users with higher levels of technology anxiety use fewer self-service technologies, and that technology anxiety is a strong determinant to actual usage of self-service technologies (Meuter et al., 2003). Lee et al. (2010) conducted a similar study to explore how demographics and consumer traits influence consumers' intention to use retail self-service checkouts. The results showed that gender indirectly influences intention to use self-checkouts through technology anxiety and technology innovativeness, since women have greater levels of technology anxiety while men have higher levels of technology innovativeness. The results also showed that older consumers tend to have more technology anxiety and are therefore less likely to use self-checkouts (Lee et al., 2010). Larson (2019) conducted a study to explore how sociodemographic aspects and different attitudes affected shoppers' interest in using self-checkouts in American Supermarkets. The key findings were that higher age and technological anxiety has a negative influence on shoppers' interest in using self-checkouts (Larson, 2019).

Table 1. Literature on customers' response to self-service technologies

Author	Theory	Technology	Sample	Variables
Dabholkar & Bagozzi (2002)	Attitudinal Model	Touch-screen ordering in fast food restaurants	USA (online survey)	Ease of use, performance, fun (iv), attitude toward using (med), intention to use (dv), self-efficacy, inherent novelty seeking, need for human interaction, self-consciousness, perceived waiting time, social anxiety (mod).
Dabholkar et al. (2003)	Attribute Based Model	Self-scanning	USA (in store survey)	Speed, ease of use, reliability, enjoyment, control (iv), intention to use (dv), preference of human interaction, store crowding, number of items (mod)
Weijters et al. (2007)	TAM	Self-scanning	Europe (in store survey)	Usefulness, ease of use, reliability, fun, newness (iv), attitude toward SST (med), SST use (dv), education, age, gender (mod).
Elliott et al. (2012)	TAM & TRI	Self-scanning	USA (online survey)	Technology readiness (iv), usefulness, ease of use, reliability, fun (med), attitude toward using SST (dv).
Demirci Orel &	SSTQUAL	Self-checkout	Turkey (in store survey)	Functionality, enjoyment, security, assurance, design, convenience, customization (iv), service quality, satisfaction (med), loyalty (dv).

Kara (2014)				
Fernandes & Pedroso (2017)	Attribute Based Model & SSTQUAL	Self-checkout	Portugal (in store survey)	Speed, ease of use, reliability, fun/entertainment, control (iv), perceived quality, satisfaction (med), repatronage intentions (dv), consumer traits, frequency of use (mod)
Meuter et al. (2003)	n.a.	Several self-service technologies	USA (online survey)	Technology anxiety, gender, age, education, income (iv), self-service technology usage, satisfaction, wom intentions, repeat usage intentions, attributions (dv)
Lee et al. (2010)	n.a.	Retail self-service checkout	USA (online survey)	Technology anxiety, need for interaction, technology innovativeness, gender, age, education, income (iv), intention to use (dv)
Larson (2019)	n.a.	Self-checkout	USA (online survey)	Technology anxiety, gender, age, education, income, ethnicity, marital status, parent, green attitudes, privacy concerns, risk attitudes, speed preferences, impulse behavior, social desirability bias

Note: iv = independent variables, dv = dependent variables, med = mediating variables, mod = moderating variables. n.a. = no main theory presented.

2.1.2. Customers' response to artificial intelligence solutions in grocery stores

The existing literature on customers' responses to artificial intelligence in grocery stores mostly revolves around unmanned stores enabled by AI, where Amazon Go and their Just Walk Out technology (JWO) is the most frequently used example. A theoretical model that has been applied in several studies about unmanned stores enabled by AI is the Unified Theory of Acceptance and Use of Technology model (UTAUT) by Venkatesh et al. (2003). The UTAUT model is a development of TAM and suggests that performance expectancy, effort expectancy, social influence and facilitating conditions are antecedents to behavioral intention and usage behavior (Venkatesh et al., 2003). In a study about customers' adoption of autonomous shopping systems, Sharma et al. (2022) extended the UTAUT model by adding trust as a mediator and privacy concern as a moderator. The results showed that all four antecedents in the UTAUT model have a positive impact on perceived trust in autonomous shopping systems, and that trust positively influences customers' shopping intentions. The study also confirmed that the relationship between performance expectancy and consumers' trust becomes weaker when customers are more concerned about privacy (Sharma et al., 2022). Ponte & Bonazzi (2023) applied the UTAUT model in a study about customers' acceptance of new retail technologies. They found that Smart Cart was the most accepted technology, Scan and Go the second most accepted and JWO technology the least accepted. For

Smart Cart and Scan and Go, the respondents were worried about the loss of human contact with service employees, but they were not worried about privacy risks. For the JWO technology however, most of the respondents were concerned about privacy and more than 50% of the respondents answered that they do not want to use JWO technology. The authors concluded that the results show a clear refusal and distrust towards the JWO technology (Ponte & Bonazzi, 2023). C.-Y. Lin (2022) applied the UTAUT model in a study about consumers' perceptions and attitudes to unmanned shops and found that performance, effort expectancy, social influence and perceived value have a positive effect on consumer attitudes. In addition, the results showed that perceived risk has a negative direct effect on consumers' patronage intentions (C.-Y. Lin, 2022).

Esch et al. (2021) compared consumer patronage likelihood between JWO technology, self-checkouts and human checkouts. The authors applied the Technology Threat Avoidance Theory (TTAT) (Liang & Xue, 2009) which explains how people's vulnerability towards technology threats influence their motivation to avoid technology. Esch et al. (2021) found that customers' purchase intent was higher for JWO technology than for traditional self-checkouts and human checkouts. The results also showed that AI-enabled in-store communication led to higher purchase intent when customers perceived the AI-technology as non-threatening. However, the positive effect on purchase intent became insignificant when customers found the AI-technology to be more threatening (Esch et al., 2021). Inman & Nikolova (2017) conducted a study about six new retail technologies and proposed a retailer adoption decision framework. According to their proposed framework, customers' attitude and privacy concerns are expected to mediate the relationship between retail technologies and customers' behavioral intentions. Shoppers' attitude towards the technology was constructed by multiple items that measured customers' perceptions towards the technology (fairness, value, satisfaction, trust, commitment, attitudinal loyalty and intrusiveness of the technology). Privacy concern was constructed by two items measuring privacy concerns and creepiness. To explain the mediating effect of privacy concern they applied an extension of the privacy calculus model (Xu et al., 2011). According to the theory, consumers engage in a privacy calculus, meaning that they compare the costs versus the benefits they receive from disclosing their personal information (Xu et al., 2011). When Inman & Nikolova (2017) empirically tested their framework, the results showed that attitude and privacy concern mediate the relationship between retail technologies and purchase likelihood, while only attitude mediate the relationship between retail technologies and word of mouth intentions. When comparing the different technologies, the results showed that customers had better attitude and less privacy concerns for Self-checkouts and Scan and Go, compared to Smart shelf and Proximity marketing which had significantly higher privacy concerns and lower attitude (Inman & Nikolova, 2017). Wu et al. (2024) conducted a study on experiential relationship quality and shopping outcomes in unmanned stores. The results showed that value, satisfaction and trust have

a positive influence on word of mouth intentions through commitment, and that trust has a positive direct influence on patronage intentions (Wu et al., 2024).

Chang & Chen (2021) conducted a study about customers' motivation to shop in BingoBox, which is an unmanned store enabled by AI on the Asian market. The authors applied TRI and the Hedonic Information Systems Acceptance Model (HISAM) by van der Heijden (2004), which is a development of TAM that adds perceived enjoyment as a variable that influences intention to use. Chang & Chen (2021) found that perceived ease of use affects perceived usefulness and perceived enjoyment, and that these factors have a direct influence on shopping intention. The results also showed that perceived ease of use has a stronger impact on perceived usefulness and shopping intention for customers with a higher level of technology readiness (Chang & Chen, 2021). Park & Zhang (2022) conducted a study about users of BingoBox and TaoCafé, which is another unmanned store by the company Alibaba. In their study, they applied TRI and combined it with the Technology Paradox Theory (PT) by Mick & Fournier (1998). The PT theory considers the conflict between customers' positive and negative emotions and perceptions of technology which can lead to paradoxical attitudes (Mick & Fournier, 1998). The results from Park and Zhang's study showed that customers' insecurity regarding the technology increased chaos, perceived inefficiency, and privacy protection, while customers discomfort decreased perceived efficiency and control (Park & Zhang, 2022).

Table 2. Literature on customers' response to artificial intelligence in grocery stores

Author	Theory	Technology	Sample	Variables
Sharma et al. (2022)	UTAUT	Autonomous shopping systems	Fiji (Online survey)	Performance expectancy, effort expectancy, social influence, facilitating conditions (iv), trust (med), shopping intention (dv), privacy concern (mod).
Ponte & Bonazzi (2023)	UTAUT	Just walk out technology, Scan and Go, Smart Cart	Italy (online survey)	Performance expectancy, effort expectancy, facilitating conditions, perceived risk (iv), behavioral intention (dv), gender, age, education (mod).
C.-Y. Lin (2022)	UTAUT	Intelligent unmanned convenience store	Taiwan (online survey)	Performance expectancy, effort expectancy, social influence, perceived value, perceived risk (iv), attitude (med), purchase intention (dv), experience (mod).
Esch et al. (2021)	TTAT	Just walk out technology, self-checkout, human checkouts	USA (online survey)	Checkout type (iv), in-store communication stimulation (med), store atmosphere evaluations, purchase intent (dv), consumers perceived AI threat (mod).

Inman & Nikolova. (2017)	Privacy Calculus	Self-checkout, Scan and Go, Mobile Apps, Smart Shelf, Que Vision, Proximity Marketing	USA (online survey)	Retail technologies (iv), perceived fairness, value, satisfaction, trust, commitment, attitudinal loyalty, intrusiveness of the technology, privacy concern (med), retail patronage, word of mouth intentions (dv).
Wu et al. (2024)	n.a.	Smart unmanned store	China (in-store survey)	Service innovation, process innovation, marketing innovation, organizational innovation (iv), value, satisfaction, commitment, trust (med), wom intentions, patronage intentions (dv).
Chang & Chen (2021)	HISAM & TRI	BingoBox	China (in-store survey)	Perceived ease of use (iv), perceived usefulness, perceived enjoyment (med), shopping intentions (dv), technology readiness (mod).
Park & Zhang (2022	TRI & PT	BingoBox & TaoCafé	China (online survey)	Optimism, innovativeness, discomfort, insecurity (iv), efficiency, control, private, inefficiency, chaos, public (med), attitude, intention to use (dv).

Note: iv = independent variables, dv = dependent variables, med = mediating variables, mod = moderating variables. n.a. = no main theory presented.

2.1.3. Customers' response to online behavioral advertising

Due to the lack of articles that focus on the surveillance and transparency aspect of AI in grocery stores, we searched for literature in related fields and found several studies on customers' response to Online Behavioral Advertising (OBA). Customers who are tracked and monitored online by advertisers and confronted with targeted and personalized advertisements experience a similar situation as customers who are tracked and monitored in grocery stores and confronted with AI-assisted surveillance in self-checkouts. In both cases, companies track their customers with advanced technologies, sometimes without customers' knowledge which could potentially lead to similar emotional responses and behavioral outcomes. In a literature review on articles about OBA by Boerman et al. (2017), the authors develop and propose a framework based on previous literature that identifies and integrates variables and theories that could explain consumer responses toward OBA. In their framework, the authors propose that the level of personalization of the ad and the advertiser's transparency about data collection have an influence on customers' perceptions of the ad. Some of the suggested perceptions are trust towards the advertiser, privacy concerns, feelings of vulnerability and perceived intrusiveness. These perceptions are then expected to influence outcomes such as purchase intention, acceptance, and advertising avoidance (Boerman et al., 2017).

Bleier & Eisenbeiss (2015) conducted a study to investigate how trust moderates the impact of ad personalization on consumers' internal and external responses. They applied the Stimulus-Organism-Response Model (S-O-R model) by Mehrabian & Russell (1974). The S-O-R model explains how environmental stimuli influence an organism's internal state, which ultimately influences their external response (Mehrabian & Russell, 1974). Bleier & Eisenbeiss (2015) also used the Theory of Psychological Reactance (Brehm, 1966) to explain why customers can perceive personalized advertisement as intrusive and react negatively. The theory suggests that when people are exposed to a stimulus that threatens their freedom of choice, they will react negatively and try to restore their freedom (Brehm, 1966). Bleier & Eisenbeiss (2015) found that for less trusted retailers, personalized ads are not perceived as more useful and leads to increased reactance (intrusiveness) and privacy concerns. Furthermore, the study showed that less trusted retailers have lower click-through intentions compared to trusted retailers (Bleier & Eisenbeiss, 2015). van Doorn & Hoekstra (2013) conducted a study about the role of intrusiveness in online advertising. They found that more personalized ads increase feelings of intrusiveness which negatively affects purchase intentions. They also confirmed that people with high privacy concerns have lower purchase intentions when exposed to these ads (van Doorn & Hoekstra, 2013).

Miyazaki (2008) investigated the effect of website cookie disclosures on consumer trust, privacy concerns and anticipated patronage. Miyazaki used the Social Contract Theory (Dunfee et al., 1999) to explain the effects of transparency on consumer trust. Miyazaki (2008) argued that advertisers form an implied social contract with consumers when disclosing the collection of personal data, but when companies do not disclose the collection of personal data or handle the personal data irresponsibly, they are violating the social contract which creates a breach of trust. Miyazaki's study showed that when there is no cookie disclosure, the implied social contract appears to be breached, which results in lower trust and intention to use. However, the negative reactions consumers have towards cookie use are significantly reduced by cookie disclosures. The results also showed that consumers' online experience and desire for privacy have a moderating effect on reactions to cookie use (Miyazaki, 2008). Stanaland et al. (2011) conducted a study about the effect of online "privacy trustmarks", which is a symbol that informs visitors that the website is part of a program that protects consumers privacy. The results of the study revealed that "privacy trustmarks" have a positive effect on consumers' perceptions of the trustworthiness of the advertiser and decrease privacy concerns about the advertiser, which lead to more positive patronage intentions and intentions to recommend (Stanaland et al., 2011).

Aguirre et al. (2015) conducted a study to investigate how personalized advertisement and information disclosure impacts consumers' vulnerability and click-through intentions. They applied the Psychological Ownership Theory (Pierce et al., 2001) to

explain how the degree of personalization can lead to an affective vulnerability experience. The theory suggests that when consumers lose their sense of ownership over a situation, feelings of vulnerability can arise. If firms engage in certain actions that the consumer have no control over, they may feel vulnerable, powerless, and even exploited (Pierce et al., 2001). Aguirre et al. (2015) found that consumers who are unaware that their data is being collected, feel more vulnerable when confronted with a personalized advertisement which leads to lower click-through intentions. In contrast, firms who are transparent about their information collection, receive greater clickthrough intentions as a response to more personalized advertisements (Aguirre et al., 2015).

Table 3. Literature on customers' response to online behavioral advertising

Author	Theory	Sample	Variables
Bleier & Eisenbeiss (2015)	S-O-R Model, Theory of Psychological Reactance	Germany (online-survey)	Degree of ad personalization (iv), perceived usefulness, reactance (intrusiveness), privacy concerns (med), click-through rate (dv), trust in the retailer (mod)
Van Doorn & Hoekstra (2013)	n.a.	Netherlands (online-survey)	Customization of targeted advertisement (iv), intrusiveness (med), purchase intentions (dv), privacy concern (mod).
Miyazaki (2008)	Social Contract Theory	USA (survey)	Cookie disclosure, no cookie disclosure (iv), consumer trust, intention to use, intention to recommend (dv), desire for privacy, online experience (mod).
Stanaland et al. (2011)	n.a.	USA (online-survey)	Privacy trustmark, no privacy trustmark (iv), advertiser ethics, trust in advertiser, privacy concerns, patronage intentions, intention to recommend (dv), desire for privacy, attitudes towards advertising (mod).
Aguirre et al. (2015)	Psychological Ownership Theory	Netherlands & USA (online-survey)	Degree of personalization (iv), perceived vulnerability (med), click-through intentions (dv), disclosure of information collection (mod).

Note: iv = independent variables, dv = dependent variables, med = mediating variables, mod = moderating variables. n.a. = no main theory presented.

2.1.4. Identified research gap

AI solutions for theft prevention in grocery stores have received criticism for treating customers as suspects (Taylor, 2023), discriminating poor people (Das, 2024), lacking transparency regarding the collection and use of personal data and for tracking and monitoring customers every move which can create a feeling of being constantly

watched (Enescu, 2024). Based on the criticism, it is easy to jump to the conclusion that increased surveillance and the lack of transparency are critical aspects to why customers might be hesitant to this technology. Despite this, we could not find any existing literature on AI in grocery stores that explore customers' response to increased AI surveillance and the lack of transparency. Instead, previous literature on customers' response to AI in grocery stores mostly revolves around customer acceptance of unmanned stores enabled by AI. To fill this research gap, we aim to explore customers' responses to different degrees of AI-assisted surveillance in self-checkouts. In addition, our study will also explore if transparency regarding theft-prevention has a positive effect on customers' responses.

In the search for a suitable theory, we learned that previous research about customers' responses towards self-checkouts and AI in grocery stores mainly applied theories that are extensions or developments of TAM. These theories describe how customers evaluate technology where the most frequently tested variables are usefulness, ease of use, performance and fun. These evaluations are then expected to influence customers' attitude towards using the technology and customers' intention to use the technology (TAM, UTAUT, HISAM, Attitudinal model, Attribute based model). While all these theories are useful in explaining customers' acceptance toward technologies they use voluntarily, they are not as suitable for explaining customers' response to technologies they are exposed to. The added element of AI-assisted surveillance in the self-checkout might evoke negative feelings that previous studies about self-checkout technology had no reason to test. Some previous studies included variables that are relevant for this study such as privacy concern and trust, but these were often added as an extension to the existing theory.

Because of this, we searched for more suitable theories in related research fields. Several studies about online behavioral advertising focused on customers' psychological responses to being tracked and how transparency influences their behavioral intentions. Bleier & Eisenbeiss (2015) applied the Simulus-Organism-Response Model (S-O-R model) by Mehrabian & Russell (1974) to explore how different degrees of ad personalization influence consumers' internal states, which influence their external responses. Since the purpose of this thesis was to explore whether different degrees of AI-assisted surveillance influence customers' responses, we decided to apply the S-O-R model as the main theory for this study.

2.2. Theoretical framework

2.2.1. Stimulus-Organism-Response model

The S-O-R Model by Mehrabian & Russell (1974) is a classic model in the field of environmental psychology. The model explains how environmental factors (stimulus) influence the internal state of an organism (organism), which in turn influence external

responses in terms of approach-avoidance intentions (response). Mehrabian and Russel proposed that the internal state consist of three basic emotional dimensions, referred to as the PAD typology (Pleasure-Displeasure, Arousal-Nonarousal, and Dominance-Submissiveness). According to the model, these emotions mediate the relationship between stimulus and avoidance and approach behaviors in any environment (Mehrabian & Russell, 1974). Donovan & Rossiter (1982) applied and empirically validated the S-O-R model in a retail setting, where the external response variables were adapted to fit retail shopping intentions. The S-O-R model later received criticism for claiming that three emotional dimensions was enough to explain the range of possible variations in consumers' internal reactions (Eroglu et al., 2001). Eroglu et al. proposed an extension of the S-O-R model by adding cognitive states to the organism component and two individual traits as moderators. Cognitive state was described as everything that goes on in the consumers' minds concerning acquisition, processing, retention and retrieval of information (Eroglu et al., 2001). In 2003, the extended model was empirically tested in an online store atmosphere and the results supported the model proposition that environmental stimuli influence consumers' affective and cognitive states, which influence their shopping behaviors (Eroglu et al., 2003).

In this thesis, the S-O-R model will be applied and empirically tested in a new setting (self-checkout area). The model will also be modified to fit the new context by adding new variables that are expected to capture customers' affective and cognitive states when exposed to AI-assisted surveillance and transparency. According to the S-O-R model, the selected variables are expected to have the following effects: The degree of AI-assisted surveillance in self-checkouts (Stimulus) influence customers' affective and cognitive states (Organism), which ultimately influence customers' behavioral intentions (Response). Transparency is expected to have a moderating effect. The sections below provide a short description of the selected variables and are followed by the development of hypotheses.

Stimulus: Degree of AI-assisted surveillance

The environmental stimulus for this study is the degree of AI-assisted surveillance in self-checkouts. The AI technology depicted in this experiment is based on available technologies today. The selected technology does not use facial recognition and does not collect or use biometric data. Instead, the technology used in this study applies image recognition software that is enhanced by AI, which can amongst other things capture unsuccessful scans in self-checkouts with overhead security cameras recording the interaction. This experiment aims to compare customers' responses to different degrees of AI-assisted surveillance with their responses to traditional theft prevention checks without AI. Respondents will therefore be randomly exposed to scenarios with three different degrees of AI-assisted surveillance, ranging from non-existent degree to high degree. (1) The non-existent degree of AI-assisted surveillance consists of a scenario without AI, where a randomized control is performed by human staff at the

self-checkout. This scenario is inspired by existing solutions from Swedish grocery stores. (2) The moderate degree of AI-assisted surveillance consists of a scenario where AI detects an unsuccessful scan at the self-checkout and alerts a staff member. (3) The high degree of AI-assisted surveillance consists of a scenario where AI detects an unsuccessful scan at the self-checkout, alerts a staff member, and replays a recorded video footage of the customer performing the unsuccessful scan on the self-checkout screen. The moderate and high degree are based on the same AI-technology, but since the high degree includes an additional element in the form of recorded video footage, we define that scenario as the highest degree of AI-assisted surveillance in this experiment.

Organism: Customers emotions and perceptions

According to the S-O-R model, the internal state of the organism mediates the relationship between stimuli and responses, which means that the selected variables are expected to act as mediating variables. This study includes both affective and cognitive states in line with the extended version of the S-O-R model by Eroglu et al. (2001). The reason for this is the need to cover not only emotions that can occur due to the surveillance, but also perceptions of the store and the self-checkout system which require more thinking than pure emotional responses. The internal states investigated in this study were selected based on the literature review and the discovered research gap. The selected variables are (1) feelings of vulnerability, (2) perceived intrusiveness, (3) trust towards the store and (4) privacy concerns regarding the store.

Response: Customers behavioral intentions

The final outcome of the S-O-R model is the external response which is customers' approach-avoidance intentions. Donovan & Rossiter (1982) who set the model in a physical store environment, adapted the approach-avoidance intentions to fit retail shopping intentions. This thesis will do a similar adaption to fit the self-checkout context. The approach-avoidance intentions have been adapted to three variables that represent customers' behavioral intentions towards the self-checkout system and the grocery store. The variables were selected based on the literature review and the expected relevance for grocers who might consider implementing AI-assisted surveillance. The selected variables are (1) Intention to use the self-checkout system, (2) Revisit intention and (3) Word of mouth intention.

Moderator: Transparency

In line with the extended S-O-R model by Eroglu et al. (2001), this study will add a moderator to the S-O-R model as well. Since the literature review revealed that unmanned stores enabled by AI have received criticism for their lack of transparency (Enescu, 2024), we intend to investigate whether information disclosure has a moderating effect on customers’ responses to AI-assisted surveillance in self-checkouts.

Drawing from the literature review on OBA, several articles found that information disclosure about data collection reduces customers' negative reactions to personalized advertisement and has a positive effect on customers' behavioral intentions (Aguirre et al., 2015; Miyazaki, 2008; Stanaland et al., 2011). Since AI-assisted surveillance is just another form of tracking customers with technology, we believe that information disclosure could reduce customers' negative response in this context as well. To test the moderating effect of transparency, two different signs were included in the scenario that represents information disclosure and no information disclosure.

2.2.2. Behavioral intentions

Intention to use the self-checkout system

In the self-service literature, multiple studies found that higher technology anxiety and higher age have a negative influence on usage intentions (Larson, 2019; Lee et al., 2010; Meuter et al., 2003). In the AI literature, Esch et al. (2021) found that customers who perceived the AI-technology as threatening, did not have a significant positive effect on purchase intent, while customers who perceived the AI-technology as less threatening had a significant positive effect on purchase intent. Given the results of these studies, it is reasonable to believe that customers who perceive the added element of AI-assisted surveillance as a threat have higher levels of technology anxiety which could lead to decreased usage intentions. In addition, Ponte & Bonazzi (2023) found that unmanned stores enabled by AI (JWO technology) were the least accepted among customers when compared with other retail technologies. In fact, more than 50% of the respondents answered that they do not want to use JWO technology due to privacy concerns. The authors concluded that the result showed a clear refusal and distrust towards JWO technology (Ponte & Bonazzi, 2023). These negative responses lead us to believe that AI-assisted surveillance in self-checkouts will decrease customers' intention to use self-checkouts. Therefore, we hypothesize:

H1a: Any degree of AI-assisted surveillance in self-checkouts will lead to lower intentions to use the self-checkout system compared to no degree of AI-assisted surveillance.

Revisit intention

In line with the previous arguments, we also believe that AI-assisted surveillance in self-checkouts will affect customers' intentions to revisit the store. In the self-service literature, Meuter et al. (2003) found that technology anxiety has a negative influence on repeat usage intention, while C.-Y. Lin (2022) found that perceived risk has a negative direct effect on consumers patronage intentions. This gives us reason to believe that AI-assisted surveillance in self-checkouts will decrease customers' intention to revisit the store. Therefore, we hypothesize:

H1b: Any degree of AI-assisted surveillance in self-checkouts will lead to lower intentions to revisit the store compared to no degree of AI-assisted surveillance.

Word of mouth intention

In line with the arguments provided above, we also believe that AI-assisted surveillance will have a negative effect on customers' intentions to recommend the store. Meuter et al. (2003) found that technology anxiety has a negative influence on word of mouth intentions. Inman & Nikolova (2017) found that customers have better attitudes toward self-checkouts without AI than retail technologies with more elements of AI and that these attitudes influence word of mouth intentions. This gives us reason to believe that AI-assisted surveillance in self-checkouts will decrease customers' intentions to recommend the store. Therefore, we hypothesize:

H1c: Any degree of AI-assisted surveillance in self-checkouts will lead to lower intentions to recommend the store compared to no degree of AI-assisted surveillance.

2.2.3. Emotions and perceptions

Feelings of vulnerability

AI in grocery stores have received criticism for treating customers as suspects (Taylor, 2023) and for tracking and monitoring customers' every move (Enescu, 2024). Drawing from the OBA literature, previous studies have confirmed that being tracked and monitored can create feelings of vulnerability. Aguirre et al. (2015) applied the Psychological Ownership Theory (Pierce et al., 2001) to explain how the degree of personalization in advertisement can lead to feelings of vulnerability. According to the theory, feelings of vulnerability can arise when consumers lose their sense of ownership over a situation. If firms engage in certain actions that consumers have no control over, they may feel vulnerable, powerless, and even exploited (Pierce et al., 2001). The study showed that consumers who are unaware that their data is being collected, feel more vulnerable when confronted with a personalized advertisement which leads to lower click-through intentions (Aguirre et al., 2015). Boerman et al. (2017) concluded that online behavioral advertisement seems to first trigger affective responses, such as feelings of vulnerability, which consequently affect consumers' behavior. Since AI-assisted surveillance in self-checkouts tracks and monitors customers in a similar way, it is reasonable to believe that AI-assisted surveillance can lead to feelings of vulnerability which influence customers' behavioral intentions. Therefore, we hypothesize:

H2a: Any degree of AI-assisted surveillance in self-checkouts will lead to higher feelings of vulnerability compared to no degree of AI-assisted surveillance.

H3a: Any degree of AI-assisted surveillance in self-checkouts will lead to higher feelings of vulnerability, leading to lower behavioral intentions.

Perceived intrusiveness

Inman & Nikolova (2017) found that perceived intrusiveness of the technology was one of the customer perceptions that mediate the relationship between retail technologies and customers' retail patronage and word of mouth intentions. van Doorn & Hoekstra (2013) showed that more personalized ads increase feelings of intrusiveness, which negatively affects purchase intentions. Bleier & Eisenbeiss (2015) found that personalized ads from less trusted retailers lead to increased feelings of intrusiveness which result in lower click-through intentions. The Theory of Psychological Reactance was applied by Bleier & Eisenbeiss (2015) to explain perceived intrusiveness, which they refer to as reactance. The theory explains that people who perceive a threat to their freedom, experience a negative emotional response called reactance (Brehm, 1966). In the context of AI-assisted surveillance, one could argue that being recorded and analyzed by AI without consent can be perceived as intrusive and pose a direct threat to one's personal freedom. Therefore, we hypothesize the following:

H2b: Any degree of AI-assisted surveillance in self-checkouts will lead to higher perceived intrusiveness of the self-checkout system compared to no degree of AI-assisted surveillance.

H3b: Any degree of AI-assisted surveillance in self-checkouts will lead to higher perceived intrusiveness leading to lower behavioral intentions.

Trust towards the store

Several articles from the AI literature have explored the relationship between trust and behavioral intentions. Sharma et al. (2022) found that trust influences customers' intention to use autonomous shopping systems. Inman & Nikolova (2017) confirmed that trust is one of the customer perceptions that mediate the relationship between retail technologies and retail patronage. Wu et al. (2024) found that high trust towards the store has a positive direct influence on patronage intentions in unmanned stores enabled by AI. Ponte & Bonazzi (2023) found that customers show a clear refusal and distrust towards unmanned stores enabled by AI (JWO technology). In the OBA literature, Bleier & Eisenbeiss (2015) found that less trusted retailers have lower click-through intentions compared to trusted retailers. In the context of AI-assisted surveillance, it is reasonable to believe that customers who are concerned about the use of AI-assisted surveillance in self-checkouts, might perceive the store as less respectful and trustworthy, which could result in lower behavioral intentions. Therefore, we hypothesize the following:

H2c: Any degree of AI-assisted surveillance in self-checkouts will lead to lower trust towards the store compared to no degree of AI-assisted surveillance.

H3c: Any degree of AI-assisted surveillance in self-checkouts will lead to lower trust, leading to lower behavioral intentions.

Privacy concerns regarding the store

Drawing from the OBA literature, several studies have confirmed that personalized advertisement increase customers' privacy concerns which lead to lower click-through intentions and purchase intentions (Bleier & Eisenbeiss, 2015; van Doorn & Hoekstra, 2013). Bleier & Eisenbeiss (2015) found that for less trusted retailers, personalized ads lead to increased privacy concerns which leads to lower click-through intentions. van Doorn & Hoekstra (2013) found that people with high privacy concerns have lower purchase intentions when exposed to personalized advertisement. Privacy concerns have been studied in the AI literature as well, where Ponte & Bonazzi (2023) found that 50% of the respondents did not want to use unmanned stores enabled by AI (JWO technology) due to privacy concerns. Sharma et al. (2022) found that the relationship between performance expectancy of autonomous shopping systems and customers' trust becomes weaker when customers are more concerned about privacy. Park & Zhang (2022) found that customers' insecurity regarding the technology used in unmanned stores enabled by AI increased chaos, perceived inefficiency and privacy protection, while customers' discomfort decreased perceived efficiency and control. Inman & Nikolova (2017) found that privacy concern mediates the relationship between retail technologies and retail patronage intentions, where customers show higher privacy concerns for retail technologies with elements of AI. Because of the studies above, we believe that AI-assisted surveillance will increase customers' privacy concerns, which will have a negative effect on customers' behavioral intentions. Therefore, we hypothesize:

H2d: Any degree of AI-assisted surveillance in self-checkouts will lead to higher privacy concerns regarding the store compared to no degree of AI-assisted surveillance.

H3d: Any degree of AI-assisted surveillance in self-checkouts will lead to higher privacy concerns, leading to lower behavioral intentions.

2.2.4. Transparency

Information disclosure and feelings of vulnerability

Aguirre et al. (2015) explored the relationship between information disclosure and feelings of vulnerability. The results showed that consumers who are not aware that their personal data is being collected, feel more vulnerable when confronted with personalized advertising, which decreases their click-through intention (Aguirre et al., 2015). This could be compared to customers in grocery stores who are not aware that they are being filmed and analyzed by AI-assisted surveillance. This might lead to feelings of vulnerability when they are suddenly confronted with AI-assisted surveillance in self-checkouts, which could decrease their behavioral intentions. However, if the grocery store informs their customers about theft-prevention checks in the self-checkouts and the reason behind it, customers might feel more prepared and

understanding when confronted with the AI-assisted surveillance. Therefore, we hypothesize:

H4a: The effect where any degree of AI-assisted surveillance in self-checkouts lead to higher feelings of vulnerability, leading to lower behavioral intentions, will be lessened by the presence of information disclosure (versus no information disclosure).

Information disclosure and perceived intrusiveness

Several studies from the OBA literature confirmed that information disclosure increases consumers' trust, while lack of information disclosure decreases consumers' trust which leads to lower behavioral intentions (Miyazaki, 2008; Stanaland et al., 2011). Bleier & Eisenbeiss (2015) found that customers who receive personalized advertisement from less trusted retailers, show increased reactance (perceived intrusiveness) which results in lower click-through intentions compared to more trusted retailers. This could apply to the context of AI-assisted surveillance as well. Customers who do not receive prior information about theft prevention checks, might perceive the AI-assisted surveillance as more intrusive compared to customers who were already informed about the theft-prevention. Therefore, we hypothesize:

H4b: The effect where any degree of AI-assisted surveillance in self-checkouts lead to higher perceived intrusiveness, leading to lower behavioral intentions, will be lessened by the presence of information disclosure (versus no information disclosure).

Information disclosure and trust towards the store

Miyazaki (2008) investigated the effect of website cookie disclosures on consumer trust, privacy concerns and anticipated patronage and used the Social Contract Theory (Dunfee et al., 1999) to explain the effects of transparency on consumer trust. Miyazaki (2008) argued that advertisers form an implied social contract with consumers when disclosing the collection of personal data, but when companies do not disclose the collection of personal data or handle the personal data irresponsibly, they are violating the social contract which leads to lower trust. The results of Miyazaki's study showed that when websites disclose the use of cookies in a privacy statement and a pop-up, consumers' trust toward the website increases which positively influences their intentions to use and recommend it. In contrast, when there is no cookie disclosure, the implied social contract appears to be breached, which results in lower trust and intention to use (Miyazaki, 2008). This leads us to believe that if grocery stores inform their customers about the theft prevention and the reason behind it, they are perceived as more trustworthy which could result in more positive behavioral intentions. Therefore, we hypothesize:

H4c: The effect where any degree of AI-assisted surveillance in self-checkouts lead to lower trust, leading to lower behavioral intentions, will be lessened by the presence of information disclosure (versus no information disclosure).

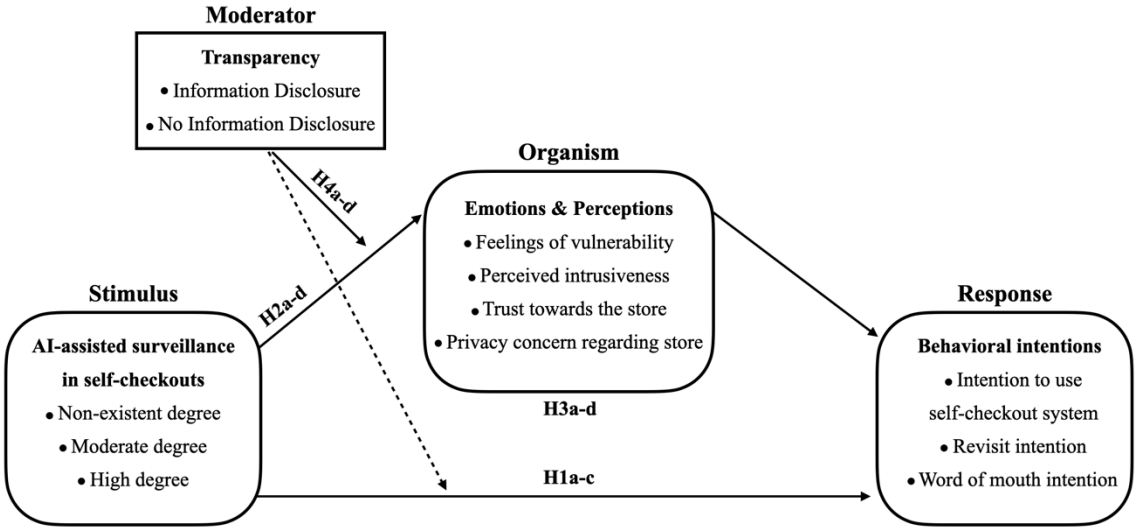
Information disclosure and privacy concern regarding the store

Several studies in the OBA literature explored how information disclosure affects customers' privacy concern. Stanaland et al. (2011) found that including privacy trustmarks on websites, decreases consumers' privacy concerns which leads to more positive behavior intentions. Miyazaki (2008) found that consumers' desire for privacy has a moderating effect on consumers' reactions towards cookie use. The Privacy Calculus Model (Xu et al., 2011) can be used to explain why customers might be willing or unwilling to disclose personal information. The model explains that customers engage in a calculus when they evaluate the costs versus the benefits of sharing their personal data in a certain situation. Consumers are more willing to disclose information if they believe that the benefits outweigh the costs (Xu et al., 2011). In the context of AI-assisted surveillance, one could argue that customers share personal information by being recorded and analyzed. Customers might perceive benefits from this such as a safer shopping environment, or perceived costs such as invaded personal space and loss of control of one's personal information. This leads us to believe that customers who are informed about the new theft prevention and the reason behind it, might be less concerned about their privacy since they could perceive it as a benefit that leads to a safer shopping environment. Therefore, we hypothesize:

H4d: The effect where any degree of AI-assisted surveillance in self-checkouts lead to higher privacy concerns, leading to lower behavioral intentions, will be lessened by the presence of information disclosure (versus no information disclosure).

2.2.5. Conceptual model

The conceptual model for this study is a modification of the S-O-R model. The modifications were made to fit the new setting, self-checkout area in grocery stores. Several new variables were added, and the conceptual model demonstrates the expected relationship between these variables according to the S-O-R model and supporting theories. The supporting theories were used in the hypotheses development to help explain specific relationships and expected outcomes. The social contract theory explains the predicted outcome of information disclosure and trust, psychological reactance theory explains intrusiveness, psychological ownership theory explains vulnerability and the privacy calculus model explains information disclosure and privacy. The expected outcomes are also based on empirical results from previous research articles about customers' response to self-service technologies, AI solutions in grocery stores and online behavioral advertising.



Note: The dashed arrow represents a moderating effect of information disclosure on the direct effect of AI-assisted surveillance on the behavioral intentions. This effect does not have any hypotheses but is included in the data analysis. The results can be found in tables 37, 40, and 43 in appendix 6.

Figure 1. Conceptual model for the study.

3. Method

3.1. Methodological considerations

The thesis is based upon a deductive approach since theory laid the foundation for further collection of data (Bryman et al., 2019). Causality was a factor that impacted the choice of doing a quantitative study due to the power of being able to explain why things are the way they are. Furthermore, the ability to provide a representative sample and be able to describe the response of the Swedish population in a generalized way required a large and broad sample which is enabled by a quantitative approach (Bryman et al., 2019). The study uses a 3x2 experiment consisting of six groups which is accomplished through using an online survey where different scenarios are displayed randomly.

3.2. Participants

The requisites were simple for participating. The research goal was looking at the perceptions of the population in terms of this new technology being introduced in grocery stores located in Sweden. Hence, we needed a way to delimit the research to people who regularly visited Swedish grocery stores. The solution became to utilize a Swedish panel company called Norstat, who distributed the survey with instructions to deliver it to people living in Sweden. Since Norstat has a requirement for their survey takers to be able to speak and understand Swedish, the authors felt that an appropriate delimitation would be to only distribute the survey in Swedish. Given the combination of these delimitations a reasonable set of requirements were in place to achieve a representative sample. Because there were six different groups, the intention was to get at least 100 respondents for each group. In communications with Norstat the goal was 720 participants, which after screening ended up being 743 (91.6%) number of usable responses to the online survey.

3.3. Structure of the survey

The survey began with a short introduction and information regarding GDPR. The respondent had to accept the GDPR terms to proceed with the survey. If the respondents declined the GDPR question they were screened. In the middle of the survey, we had an instruction manipulation check, IMC, to screen participants for inattention (Oppenheimer et al., 2009).

After the GDPR item, the respondents were faced with a scenario which then led them to either be exposed to (1) a sign with information disclosure regarding theft-prevention checks in the self-checkouts and the reason behind it or (2) a sign without information

disclosure that simply welcomes the respondents to the store. Please see section 3.4.2 for the exact text presented in each of the signs. Then the respondents were shown either of three different scenarios based on the degree of AI-assisted surveillance in the self-checkout, which ranged from high to non-existent. Please see section 3.4.2 for an exact description of the scenarios or see appendix 1 for the survey. Both the different disclosure and AI-assisted surveillance scenarios were programmed to be randomly shown an equal number of times by the randomizer function in Qualtrics. After reading the scenario the respondent was required to answer a self-checkout frequency question, and then they could answer a matrix containing the dependent variables. The IMC was then introduced where the respondent had to choose the number '4' to not be screened. After this they were asked about the mediating variables and in the end, they had to answer questions regarding consumer characteristics.

The survey consisted of 15 items to measure the mediating variables: (A) Attitude towards using self-checkout system[1], (T) trust towards the store, (PC) privacy concern regarding the store, (V) feelings of vulnerability, and (PI) perceived intrusiveness. Nine items to measure the dependent variables: (IU) intention to use the self-checkout system, (RI) revisit intention, and (WOM) word of mouth intention. Four items to measure consumer characteristics such as age, gender, education, and self-checkout frequency. One item for an IMC (Oppenheimer et al., 2009).

A seven-point Likert scale was used to measure the mediating and dependent variables (Söderlund, 2005). Our survey was a 3x2 experiment due to the three degrees of our independent variable, and our binary moderator. Therefore, we had six different groups. A bootstrap analysis was done since it is an integrated part of the PROCESS software used in the analysis and since it makes no assumption about the shape of the sampling distribution (Hayes, 2022).

3.3.1. Insights from pre-study

We conducted a pre-study on our survey using 15 participants with family and close friends where insights were collected. The ages ranged from 25 to 69 years of age. Not much needed to be changed, except substituting certain items and changing wording to make it work in Swedish. This was since all items were translated from English studies to Swedish as aforementioned. One major change was that we added multiple variables to describe the different dependent variables (intentions) due to our early-stage variables using a mixture of both word of mouth variables and loyalty variables. This change was made to make it clear which items were being measured. Some structural changes were made to make it easier for the respondent to see all alternatives as they went along. The pre-study helped secure validity, which is referenced at greater lengths in the validity section below.

[1] This variable was not considered in the final analysis.

3.4. Main study

3.4.1. Measures

To capture their responses, we used a seven-point Likert scale instead of a five-point to gather as much data as possible (Söderlund, 2005). A seven-point Likert scale also gave the respondents a chance to give a more nuanced answer.

To attain increased reliability and validity all the mediating and dependent variables had three different items to be able to calculate an average (Söderlund, 2005). Careful consideration was taken when selecting items for each variable so that all three items were from the same studies in all instances.

3.4.2. Definition of variables

As previously mentioned, all the variables were examined using a seven-point Likert scale where it ranged from Disagree Completely (SE: Instämmer inte alls) to Agree Completely (SE: Instämmer helt). All the questions were translated from English to Swedish for the survey, the English items are displayed below. Please see appendix 1 for the Swedish version of the survey with pictures included.

Moderating variable

- *No information disclosure:* The respondents are exposed to a sign with the following text “Welcome to our self-checkout. Thank you for shopping with us, we hope you have a pleasant experience.”
- *Information disclosure:* The respondents are exposed to a sign with the following text “Welcome to our self-checkout. We have been a target of theft and have therefore introduced additional measures to prevent this. This means that we have checks at the self-checkout registers. Thank you for shopping with us, we hope you have a pleasant experience.”

Independent variable

- *Non-existent degree of AI-assisted surveillance:* The respondents are exposed to a scenario where they scan their items in a self-checkout. Suddenly, the respondent receives a message on the screen that says “Are you sure you scanned all your items properly?“. The respondent presses yes, and another message appears that says, “You have been chosen for a randomized control. Please wait for the attendant". An attendant arrives and performs a recount of the items by rescanning them. The attendant discovers that the last item was not scanned properly and helps the respondent rescan it. (Pictures were used to demonstrate the messages on the self-checkout screen).
- *Moderate degree of AI-assisted surveillance:* The respondents are exposed to a scenario where they scan their items in a self-checkout. Suddenly, the

respondent receives a message on the screen that says, “Please wait for the attendant". An attendant arrives and scans their card, a message appears that says “An unsuccessful scan has been detected”. The attendant informs the respondent that the AI-system discovered that the last item was not scanned properly and helps the respondent rescan it. (Pictures were used to demonstrate the messages on the self-checkout screen).

- *High degree of AI-assisted surveillance:* The respondents are exposed to a scenario where they scan their items in a self-checkout. Suddenly, the respondent receives a message on the screen that says, “Please wait for the attendant". An attendant arrives and when they scan their card, a video is displayed on the screen that shows a recording of the customer when they perform an unsuccessful scan. The attendant informs the customer that the AI-system discovered that the last item was not scanned properly, and they help the respondent rescan it. (A video was used to demonstrate the content of the recorded footage displayed on the self-checkout screen).

Dependent variables

- *Intention to use self-checkout system (IU):* Was derived from an average of three questions. “Assuming that I have access to the self-checkout system, I intend to use it”, “Assuming that I have access to the self-checkout system, I would use it”, and “Assuming that I have access to the self-checkout system, I predict that I would use it” (Albayati, 2024).
- *Revisit intention (RI):* Was derived from an average of three questions. “If I have the option, I would gladly return to this store in the future”, “As long as this store offers the same level of service as it did during this visit, I would prefer this store over other places”, and a reverse coded item “I would not visit this store in the future” (Holmqvist et al., 2019).
- *Word of mouth intention (WOM):* Was derived from an average of three questions. “I would recommend this grocery store to my friends”, “If my friends were looking for a good grocery store, I would advise them about this one”, and “It is likely that I would speak positively about this grocery store to others” (Holmqvist et al., 2019).

Mediating variables

- *Trust towards the store (T):* Was derived from an average of three questions. “I feel the store has practices that show it values me as a customer”, “I feel the store has practices that indicate respect for me as a customer”, and “I feel the store can be relied on to be honest” (Stanaland et al., 2011).
- *Privacy concern regarding the store (PC):* Was derived from an average of three questions. “I feel this store is serious about consumer privacy”, “I feel this store is likely to treat consumers fairly with respect to privacy issues”, and a reverse

coded item “I feel this store is likely to violate privacy standards” (Stanaland et al., 2011).

- *Feelings of vulnerability (V):* Was derived from an average of three questions. “This self-checkout system made me feel exposed”, “This self-checkout system made me feel unprotected”, and “This self-checkout system made me feel vulnerable” (Aguirre et al., 2015).
- *Perceived intrusiveness (PI):* Was derived from an average of three questions. “This self-checkout system is disturbing”, “This self-checkout system is intrusive”, and “This self-checkout system is unwelcome” (Bleier & Eisenbeiss, 2015).

Apart from the described variables we had four variables for consumer characteristics which can be seen in the full survey in appendix 1.

3.5. Data collection and analysis

3.5.1. Data collection

The data collection was performed with the help of professional Swedish panel company Norstat (*Norstat*, n.d.), where approximately 811 responses were collected. The data collection period ranged from the 12th of March till 25th of March where the survey was only distributed using Norstat’s services. 811 (100%) responses were collected from Norstat’s panel. The GDPR acknowledgement question screened 30 (3.7%) respondents and the IMC filtered out 1 (0.1%) respondent leaving us with a total amount of 743 (91.7%) respondents after also screening for unfinished surveys which amounted to 37 (4.6%) respondents. 91.7% finished the survey, meaning that 8.3% did not finish the survey (including declined GDPR respondents).

3.5.2. Analysis

After collecting the data with the use of online service Qualtrics, the data was downloaded and run through excel. The descriptive statistics, means, standard deviations, and Cronbach’s alpha test were calculated using excel. The statistical analyses and the crosstabs chi-square test were performed using SPSS 29.0.

One-way ANOVA

To test hypotheses H1a-c and H2a-d, One-way ANOVA tests were ran using SPSS. The one-way ANOVA test probes the direct effect between two variables. H1a-c probes the direct effect between the independent variable, AI-assisted surveillance, and the three different dependent variables, intention to use, revisit intention, and wom intention. H2a-d probes the direct effect between the independent variable and the four different mediators, trust, privacy concern, feelings of vulnerability and perceived intrusiveness.

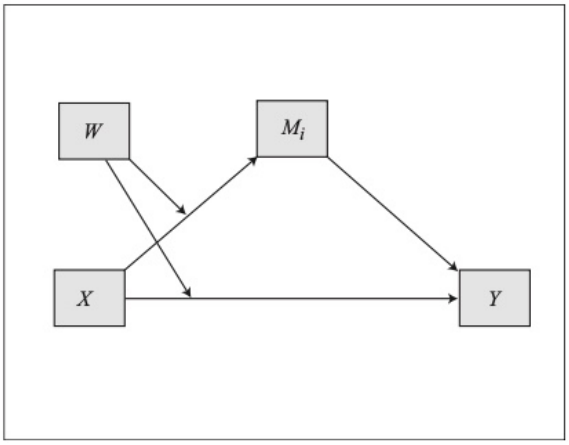
Due to the structure of the conceptual model (see figure 1) a Structural Equation Modeling (SEM) approach was adopted. To perform the SEM analysis an alternative approach of using PROCESS for SPSS by Andrew F. Hayes (2022) was employed.

PROCESS macro model 4

To test the mediation hypotheses (H3a-d), the PROCESS macro (model 4) was used. The mediation hypotheses H3a-d test whether any degree of the independent variable, AI-assisted surveillance, will lead to higher or lower reported values of the mediator which in turn leads to lower values of the three dependent variables, the behavioral intentions. PROCESS macro (model 4) probes whether mediation takes place. Due to the nature of the independent variable, it was classified as a multicategorical antecedent variable in PROCESS. The coding group used was Indicator which makes X into dummy variables, where X = 1 is the control group. Two groups are formed, X1 where X = 1 (AI-assisted surveillance is non-existent) is compared with X = 2 (AI-assisted surveillance is moderate). And X2 where X = 1 is compared with X = 3 (AI-assisted surveillance is high). Both model 4 and 8 can handle multicategorical variables (Hayes, 2022; Hayes & Preacher, 2014).

PROCESS macro model 8

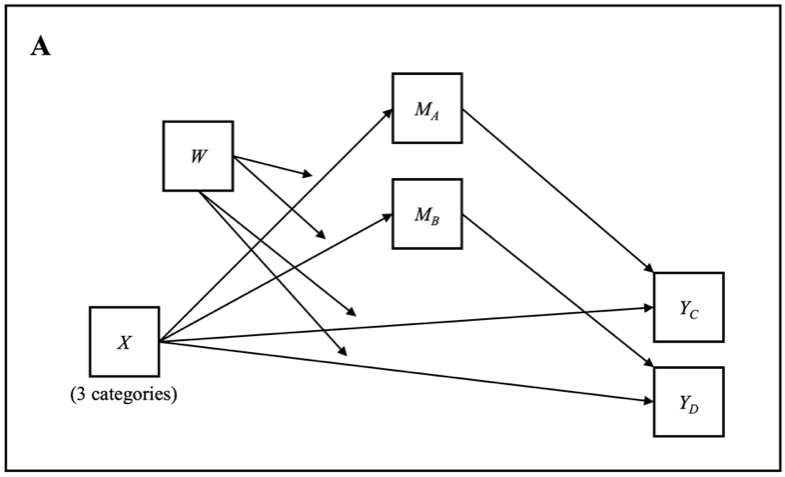
To test the moderated mediation hypotheses (H4a-d), the PROCESS macro (model 8) was deemed sufficient due to its ability to test multiple parallel mediators (Hayes, 2022). The moderated mediation hypotheses H4a-d test whether the proposed effect of mediation stated in H3a-d can be lessened by introducing information disclosure (moderator). However, model 8 also provides an output whether the moderator (information disclosure) influences the direct effect, meaning the relationship between the independent variable and the dependent variable. This effect lacks hypotheses, but the results are reported in appendix 6. PROCESS macro (model 8) was selected since a parallel mediation model where one could gather an estimation of the direct and indirect effect was needed. Further, PROCESS macro (model 8) considers the moderators effect on both the indirect a-path (independent variable to mediator) and the direct c´-path (independent variable to dependent variable).



Note: Depicted is the PROCESS macro (model 8) from Andrew F. Hayes book (2022). Variable description: X = Independent Variable; W = Moderator; M_i = Mediator$_i$; Y = Dependent Variable.

Figure 2. PROCESS macro (model 8)

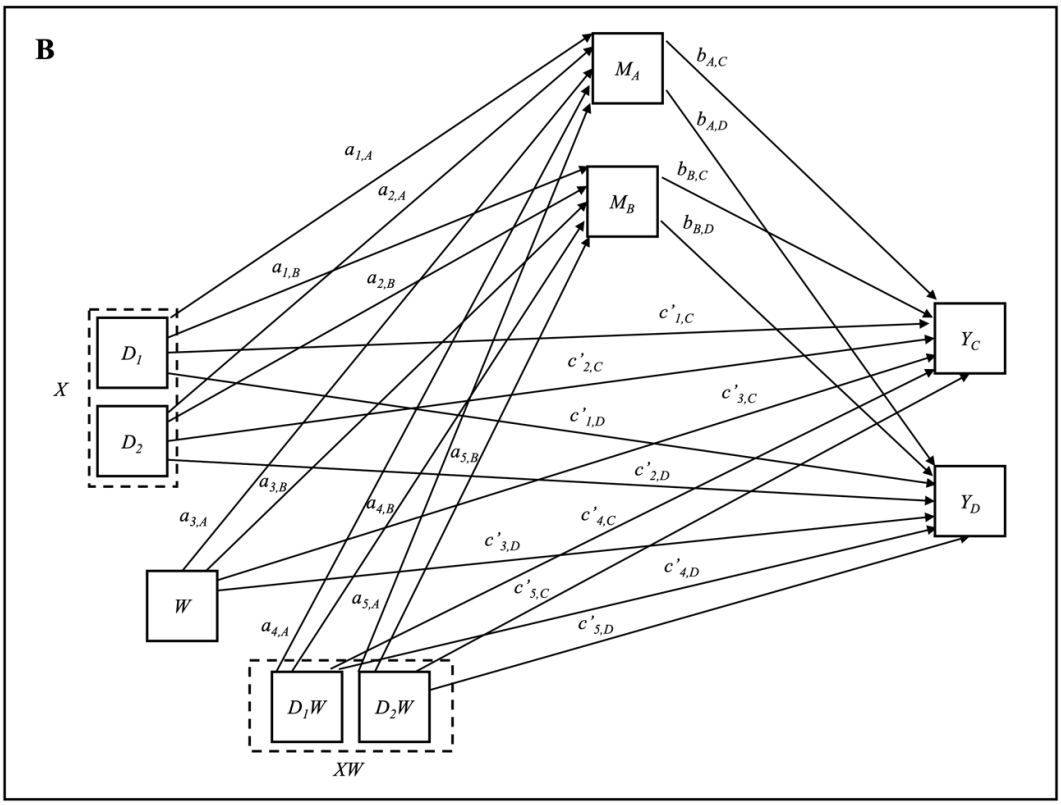
Three different analyses were performed for both PROCESS macro (model 4 & 8) since the conceptual model had three dependent variables to account for. Bootstrapping was used to obtain 95% confidence intervals for indirect effects for both model 4 and 8. All the PROCESS macro (model 4 & 8) tests were done using 5000 bootstrap samples. For model 8 this involved testing for conditional direct and indirect effects at different levels of the moderator (W = 0, meaning without information disclosure; and W = 1, meaning with information disclosure).



Note: Depicted is our conceptual diagram of a conditional process model with a multicategorical antecedent *X* with three categories and a continuous moderator of the *X* → *M* and *X* → *Y* paths inspired and based upon PROCESS macro (model 8) from Andrew F. Hayes book (2022) with two mediators and

two dependent variables. Variable description: X = Multicategorical Independent Variable; W = Moderator; M_i = Mediator$_i$; Y_i = Dependent Variable.

Figure 3. Conceptual diagram of conditional process model with multicategorical antecedent (model 8)



Note: Depicted is our statistical diagram of a conditional process model with a multicategorical antecedent *X* with three categories and a continuous moderator of the *X* → *M* and *X* → *Y* paths inspired and based upon PROCESS macro (model 8) from Andrew F. Hayes book (2022) with two mediators and two dependent variables. This model will be used as a reference, whereas the model tested in this thesis paper uses four mediators and three dependent variables.

Figure 4. Statistical diagram of conditional process model with multicategorical antecedent (model 8)

3.6. Reliability and validity

3.6.1. Reliability

Reliability revolves around the ability to repeat a study's outcomes consistently (Bryman et al., 2019). Cronbach's alpha was used to analyze the variables' internal reliability (Söderlund, 2005). Our frame of acceptable threshold value was 0.7 (Söderlund, 2005), which all the following variables passed (see table 4). After this value was calculated, a new value was calculated for each variable by taking the

average off the three items corresponding to each variable. For the remaining questions regarding consumer characteristics such as Age, Gender, Education, and Self-checkout frequency the Cronbach's alpha cannot be calculated. There we used insights from the pre-study and common formats used in previous peer-reviewed research in the same domain which strengthens the reliability of the thesis. A crosstabulation chi-square test was performed to see whether the distribution of the consumer characteristics variables between the three groups for the independent variable were adequate (see table 5).

Table 4. Cronbach's alpha

Variable	n	Cronbach's alpha	No of items
Trust	743	0.917	3
Perceived Intrusiveness	743	0.930	3
Vulnerability	743	0.938	3
Privacy Concern	743	0.722	3
Intention to Use	743	0.978	3
Revisit Intention	743	0.720	3
Word of Mouth	743	0.945	3

Note: In total, after screening procedures, we had 743 respondents. A Cronbach's alpha is considered sufficient when the number is higher than 0.7, a condition all the variables fulfill.

Table 5. Crosstabulation chi-square test for independent variable

Variable	χ^2	df	p
Age	6.942	14	.937
Gender	3.508	6	.743
Education	13.188	10	.213
Frequency	15.780	12	.202

Note: The results shown are crosstab tests comparing the independent variable AI-assisted surveillance degree compared to the consumer characteristics variables in the variable column. A significant result indicates that either variable was unevenly distributed in the three groups for the independent variable. None of the tests were significant which means that there was apt randomization between groups based on the independent variable and all the variables in the variable column.

Since none of the tests came back statistically significant in table 5, one can determine that the distribution between the three categories of the independent variable were satisfying when looking at these four variables.

3.6.2. Validity

Measurement validity is concerned with if what is being measured truly measures what one sets out to measure (Bryman et al., 2019). When conducting quantitative research measurement validity, often referred to as *construct validity*, is primarily applied (Bryman et al., 2019). To provide measurement validity all the items for the mediating and dependent variables were acquired from other studies in related research domains

which had tested multiple items for the same variable to conclude the best ones to measure. In other instances, there were several reviewed studies where versions of the same items had been recycled over multiple studies with successful results. *Face validity* was garnered through a pre-study where people did the survey and then were asked the relevance of the different questions given the variable being examined (Bryman et al., 2019). *Discriminant validity* was also examined during the pre-study, which is why the thesis went from having one dependent variable to three different ones to ensure the constructs measured what needed to be measured (Bryman et al., 2019).

4. Results

When interpreting the results, note that all measured variables except the consumer characteristics were measured using a seven-point Likert scale. One denotes “Disagree completely”, four denotes “Neither agree nor disagree”, and seven denotes “Completely agree”. All questions except perceived intrusiveness (PI) and feelings of vulnerability (V) were formulated in a positive way, meaning that a higher mean equals a more positive response for these variables. For the other two variables, intrusiveness and vulnerability, a high mean indicates a negative response. For further clarification, please see section 3.4.2 for the questions again. Thanks to the help of Norstat we managed to get a well-rounded population in terms of consumer characteristics which aids the credibility of our results.

4.1. Descriptive statistics

Table 6. Descriptive statistics over respondents

Survey N = 743	No Information Disclosure (n = 369) Degree of AI Surveillance = 1, 2, 3			With Information Disclosure (n = 374) Degree of AI Surveillance = 1, 2, 3		
Variable	1 (n=122)	2 (n=132)	3 (n=115)	1 (n=126)	2 (n=116)	3 (n=132)
Age						
18-24	11	10	10	14	11	14
25-34	29	23	25	25	25	30
35-44	19	24	20	20	24	20
45-54	16	15	11	16	14	17
55-64	18	26	28	20	19	22
65-74	15	17	13	22	15	13
75-84	14	16	8	9	8	15
85 and above	0	1	0	0	0	1
Gender						
Prefer not to say	1	1	1	0	0	0
Non-binary / Third gender	0	0	0	0	0	1
Female	68	77	52	65	59	70
Male	53	54	62	61	57	61
Education						
Less than high school	8	12	5	10	9	5
High school	55	52	50	48	42	55
Bachelor's degree	31	33	27	28	32	41
Master's degree	15	11	19	28	17	17
Doctoral degree	0	4	0	3	4	5
Professional degree	13	20	14	9	12	9
Self-checkout frequency						
Not at all	12	17	14	19	14	18
Less than once a week	23	25	31	19	28	28
About once a week	36	27	28	35	26	30
2 or 3 times a week	26	42	26	37	27	34
4 to 6 times a week	21	16	14	14	17	19
About once a day	2	5	2	1	4	3
More than once a day	2	0	0	1	0	0

Note: 369 respondents were not exposed to a disclosure and 374 respondents were exposed to a disclosure statement regarding theft prevention. In total, after screening procedures, we had N = 743 respondents after screening. Degree of AI Surveillance: 1 = Non-existent degree of AI surveillance; 2 = Moderate degree of AI surveillance; 3 = High degree of AI surveillance.

Table 6 presents descriptive statistics over the consumer characteristics. Here one can see all the different groups and the amount of people situated. Excel was used to derive the groups.

Table 7. Descriptive statistics over all variables

Survey N = 743			No Information Disclosure (n = 369) Degree of AI Surveillance = 1, 2, 3						With Information Disclosure (n = 374) Degree of AI Surveillance = 1, 2, 3					
			1 (n = 122)		2 (n = 132)		3 (n = 115)		1 (n = 126)		2 (n = 116)		3 (n = 132)	
Variable	Min	Max	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
A	1	8	3.84	1.90	4.09	1.87	3.81	1.77	3.83	1.86	3.71	1.78	3.81	1.93
G	1	4	1.58	0.54	1.61	0.54	1.48	0.55	1.52	0.50	1.51	0.50	1.55	0.51
E	1	6	2.86	1.34	3.02	1.53	3.01	1.37	2.94	1.29	3.01	1.38	2.92	1.21
SF	1	7	3.29	1.35	3.23	1.35	3.01	1.28	3.12	1.30	3.15	1.36	3.13	1.34
T	1	7	5.09	1.28	4.81	1.32	4.76	1.42	4.89	1.41	4.87	1.23	4.68	1.38
PI	1	7	2.77	1.59	3.07	1.59	3.39	1.63	3.09	1.64	3.36	1.59	3.30	1.69
V	1	7	2.61	1.59	2.82	1.68	3.13	1.64	2.66	1.60	2.98	1.56	3.09	1.66
PC	1	7	4.79	1.06	4.55	1.14	4.36	1.26	4.70	1.26	4.60	1.05	4.33	1.33
IU	1	7	5.12	1.79	5.09	1.77	4.99	1.73	5.01	1.76	4.97	1.67	4.87	1.92
RI	1	7	5.07	1.35	4.95	1.32	4.84	1.32	4.94	1.25	4.99	1.19	4.86	1.40
WOM	1	7	4.66	1.30	4.49	1.42	4.49	1.38	4.31	1.37	4.47	1.22	4.37	1.45

Note: 369 respondents were not exposed to a disclosure and 374 respondents were exposed to a disclosure statement regarding theft prevention. In total, after screening procedures, we had N = 743 respondents after screening. Degree of AI Surveillance: 1 = Non-existent degree of AI surveillance; 2 = Moderate degree of AI surveillance; 3 = High degree of AI surveillance. Abbreviations in the Variable column denote the following: A = Age; G = Gender; E = Education; SF = Self-checkout frequency; T = Trust; PI = Perceived Intrusiveness; V = Vulnerability; PC = Privacy Concern; IU = Intention to Use; RI = Revisit Intention; WOM = Word of Mouth.

All the individual means and standard deviations are depicted for the measured variables divided by their six groups.

4.2. Results for ANOVA

To test hypotheses H1a-c, we performed one-way ANOVA tests for our three dependent variables. To test hypotheses H2a-d, we performed one-way ANOVA tests for our four mediating variables. By performing these tests, we were able to compare the means between the three groups who were exposed to different degrees of AI-assisted surveillance in the self-checkout scenarios. The groups ranged from non-existent degree (control group), moderate degree and high degree, where each group contained 247-248 respondents. The ANOVA tests did not account for the moderator, meaning it only looked at the difference between the three degrees of AI-assisted surveillance.

Table 8. ANOVA tests results

Variable	Control μ(σ)	Moderate μ(σ)	High μ(σ)	Significance	η^2
IU	5.07 (1.77)	5.04 (1.72)	4.93 (1.83)		.001
RI	5.01 (1.30)	4.97 (1.26)	4.85 (1.36)		.003
WOM	4.48 (1.34)	4.48 (1.33)	4.43 (1.42)		.000
T	4.99 (1.35)	4.84 (1.27)	4.72 (1.40)		.007
PI	2.93 (1.62)	3.20 (1.59)	3.34 (1.66)	*, A	.011
V	2.64 (1.59)	2.89 (1.62)	3.11 (1.64)	**, A	.014
PC	4.75 (1.16)	4.57 (1.10)	4.34 (1.20)	***, A	.019

Note: Described is the mean and then the standard deviation. For the control and moderate group n = 248, whereas the high group had n = 247. All the variables except PC passed the Levene's test regarding the assumption of homogeneity. PC's Levene's Test resulted in p = .047, however, Welch and Brown-Forsythe test were both significant p<.001, after looking at Games-Howell Post Hoc Test which does not assume equal variance the significant difference was found between control and high group. The degrees of freedom for all the variables were df1 = 2; df2 = 740. The effect size, eta squared (η^2), was considered small if between .01 < η^2 < .059. The column named "Significance" denotes the following: * = p<.05, ** = p<.01, *** =p<.001. A = Post Hoc Tests show significant difference between control and high group. B = Post Hoc Tests show significant difference between control and moderate group. C = Post Hoc Tests show significant difference between moderate and high group. Abbreviations in the Variable column denote the following: IU = Intention to Use; RI = Revisit Intention; WOM = Word of Mouth; T = Trust; PI = Perceived Intrusiveness; V = Vulnerability; PC = Privacy Concern.

The ANOVA test for the mediating and dependent variables are depicted in table 8. A significant result would entail that a certain degree of AI-assisted surveillance has a direct effect on the measured variable. Perceived intrusiveness, feelings of vulnerability and privacy concern were all affected by the degree of AI-assisted surveillance when looking at the difference between the control and high group. The mean for perceived intrusiveness was higher for the group with high degree ($M_{PI, High} = 3.34$, $SD_{PI, High} = 1.66$) than the control group ($M_{PI, Control} = 2.93$, $SD_{PI, Control} = 1.62$). The mean for feelings of vulnerability was higher for the group with high degree ($M_{V, High} = 3.11$, $SD_{V, High} = 1.64$) than the control group ($M_{V, Control} = 2.64$, $SD_{V, Control} = 1.59$), meaning that as the degree of AI-assisted surveillance grew, so did the respondent's perception of intrusiveness and their feelings of vulnerability. The mean for privacy concern was lower for the group with high degree ($M_{PC, High} = 4.34$, $SD_{PC, High} = 1.20$) than the control group ($M_{PC, Control} = 4.75$, $SD_{PC, Control} = 1.16$), meaning that respondents who were exposed to the high degree had more privacy concerns since the questions were asked in a positive way. The results show support of hypotheses H2a, H2b and H2d.

Table 9. Direct effect hypotheses

H1a	Any degree of AI-assisted surveillance in self-checkouts will lead to lower intentions to use the self-checkout system compared to no degree of AI-assisted surveillance.	Rejected
H1b	Any degree of AI-assisted surveillance in self-checkouts will lead to lower intentions to revisit the store compared to no degree of AI-assisted surveillance.	Rejected
H1c	Any degree of AI-assisted surveillance in self-checkouts will lead to lower intentions to recommend the store compared the store compared to no degree of AI-assisted surveillance.	Rejected
H2a	Any degree of AI-assisted surveillance in self-checkouts will lead to higher feelings of vulnerability compared to no degree of AI-assisted surveillance.	Supported
H2b	Any degree of AI-assisted surveillance in self-checkouts will lead to higher perceived intrusiveness of the self-checkout system compared to no degree of AI-assisted surveillance.	Supported
H2c	Any degree of AI-assisted surveillance in self-checkouts will lead to lower trust towards the store compared to no degree of AI-assisted surveillance.	Rejected
H2d	Any degree of AI-assisted surveillance in self-checkouts will lead to higher privacy concerns regarding the store compared to no degree of AI-assisted surveillance.	Supported

Note: See table 8 for data.

A high degree of AI-assisted surveillance in self-checkouts lead to increased feelings of vulnerability, an increase in customers perceived intrusiveness, and an increase in customers privacy concerns. This result was statistically significant when comparing the control and high group, however, not statistically significant when comparing the moderate group with either group. This means that the moderate AI-assisted surveillance cannot be claimed to have the same impact on the aforementioned variables.

4.3. Results for mediation regression analysis (model 4)

As previously stated, the nature of the independent variable led to it being defined as a multicategorical variable for the PROCESS regression tests. Hence, the group with non-existent degree of AI-assisted surveillance (X = 1) is referred to as the control group

where X1 indicates the difference between the control group and the moderate group. Whereas X2 indicates the difference between the control group and the high group. This coding system is referred to as Indicator coding according to literature and is a form of dummy-variable coding (Hayes, 2022). A mediation has taken place if the 95% confidence intervals for tables 11, 13, and 15 does not contain zero. Important to note that only one of the confidence intervals for either mediating variable (X1 or X2) must not contain zero for the mediating effect to apply for the whole mediating variable, which is a phenomenon unique to multicategorical antecedent testing (Hayes, 2022). For full results on PROCESS model 4, see appendix 3 and 4.

All coefficients presented in the following tables are unstandardized path coefficients. The coefficients column presented in tables 10, 12, 14, are direct effects for the independent variable and mediators. The coefficients for X1 and X2 indicate the effect of moving from the baseline condition (control group) to moderate or high AI-assisted surveillance on the dependent variable, holding all other model variables constant. Hence, these coefficients are direct effects of the AI-assisted surveillance levels on the dependent variable, indicating how each level of surveillance influences the dependent variable independently of the mediators included in the model. The four mediating coefficients each describes the effect of a one-unit increase in the mediator on the dependent variable, controlling for other variables in the model including the levels of AI-assisted surveillance. These effects are understood as the contributions of each mediator to the dependent variable. For instance, a negative coefficient for perceived intrusiveness (PI) in table 10 means that for every one-unit increase in perceived intrusiveness, intention to use decreases by 0.299 units, holding all other variables constant.

Whereas the effect column in tables 11, 13, and 15 describe the indirect effect coefficient which is calculated as the product of coefficients from two paths, the independent variable to the mediator, and from the mediator to the dependent variable. The coefficient between the independent variable to the mediator shows the change in the mediator for a one-unit change in X. The coefficient from the mediator to the dependent variable indicates how much the dependent variable changes for a one-unit change in the mediator. The indirect effect is therefore a product of these two coefficients where it quantifies the change in the dependent variable brought about by the independent variable exclusively through the mediator. If X increases a mediator by a certain amount, and each unit of the mediator increases the dependent variable by another amount, the product of these two gives the total expected change in the dependent variable due to a one-unit increase in X, mediated through the mediator.

4.3.1. Intention to use the self-checkout system

Table 10. PROCESS model 4 outcome variable intention to use

IU Predictor	Coeff	t	p	95% Boot CI (LL;UL)
X1	.132	1.327	.185	(-.063;.327)
X2	.188	1.871	.062	(-.009;.384)
T	.402	8.585	.000	(.310;.494)
PI	-.299	-6.142	.000	(-.395;-.204)
V	-.042	-.877	.381	(-.135;.052)
PC	.009	.183	.855	(-.091;.109)
R^2	.620			

Note: If p < .05 for either mediating variable, then the b-path depicted in figure 4 is statistically significant. If p < .05 for X1 or X2, then the c'-path depicted in figure 4 is statistically significant.

Relative indirect effects of X on Y

Table 11. Relative indirect effect of X on intention to use

IU Predictor	Effect	BootSE	95% Boot CI (LL;UL)
X → Trust → IU			
X1	-.059	.046	(-.153;.028)
X2	-.090	.053	(-.202;.004)
X → Intrusiveness → IU			
X1	-.082	.043	(-.173;-.005)
X2	-.108	.049	(-.214;-.021)
X → Vulnerability → IU			
X1	-.011	.017	(-.051;.015)
X2	-.018	.025	(-.074;.026)
X → Privacy → IU			
X1	-.002	.001	(-.023;.020)
X2	-.004	.020	(-.042;.037)

Note: If either confidence interval for X1 or X2 does not include zero, then the mediating variable would be mediating.

In table 11, we can see that perceived intrusiveness is the only mediating variable when intention to use is the dependent variable. This means that the effect of perceived intrusiveness helps explain the effect the independent variable has on the dependent variable intention to use. More specifically, the test revealed that perceived intrusiveness mediates the relationship between AI-assisted surveillance and intention to use the self-checkout system for both X1 ($CI_{95\%}$ = [-.173;-.005]) and X2 ($CI_{95\%}$ = [-.214;-.021]) since the confidence intervals do not straddle zero. This means that the mediating effect of perceived intrusiveness is significant for the difference between the control group vs moderate degree (X1) and for the difference between the control group vs high degree (X2). The result partly supports H3b.

4.3.2. Revisit intention

Table 12. PROCESS model 4 outcome variable revisit intention

RI Predictor	Coeff	t	p	95% Boot CI (LL;UL)
X1	.114	1.546	.123	(-.031;.260)
X2	.124	1.657	.098	(-.023;.270)
T	.387	11.067	.000	(.318;.455)
PI	-.184	-5.070	.000	(-.255;-.113)
V	-.091	-2.566	.011	(-.160;-.021)
PC	.076	2.004	.045	(.002;.150)
R^2	.611			

Note: If p < .05 for either mediating variable, then the b-path depicted in figure 4 is statistically significant. If p < .05 for X1 or X2, then the c'-path depicted in figure 4 is statistically significant.

Relative indirect effects of X on Y

Table 13. Relative indirect effect of X on revisit intention

RI Predictor	Effect	BootSE	95% Boot CI (LL;UL)
X → Trust → RI			
X1	-.057	.044	(-.141;.030)
X2	-.087	.048	(-.185;.005)
X → Intrusiveness → RI			
X1	-.051	.027	(-.108;-.002)
X2	-.066	.030	(-.130;-.016)
X → Vulnerability → RI			
X1	-.023	.016	(-.059;.002)
X2	-.040	.021	(-.085;-.006)
X → Privacy → RI			
X1	-.013	.011	(-.039;.003)
X2	-.028	.017	(-.067;.001)

Note: If either confidence interval for X1 or X2 does not include zero, then the mediating variable would be mediating.

Table 13 shows that both perceived intrusiveness and feelings of vulnerability are mediating variables when looking at the dependent variable revisit intention. This means that both perceived intrusiveness and feelings of vulnerability help explain the effect of the independent variable on the dependent variable revisit intention. More specifically, the test revealed that perceived intrusiveness mediates the relationship between AI-assisted surveillance and revisit intention for both X1 ($CI_{95\%}$ = [-.108;-.002]) and X2 ($CI_{95\%}$ = [-.130;-.016]). This means that the mediating effect of perceived intrusiveness is significant when comparing the control group vs moderate degree (X1) and when comparing the control group vs high degree (X2). The test also revealed that feelings of vulnerability mediate the relationship between AI-assisted surveillance and revisit intention for X2 ($CI_{95\%}$ = [-.085;-.006]). This means that the mediating effect of

feelings of vulnerability is significant when comparing the control group vs high degree (X2). The results partly support H3a and H3b.

4.3.3. Word of mouth

Table 14. PROCESS model 4 outcome variable word of mouth

WOM Predictor	Coeff	t	p	95% Boot CI (LL;UL)
X1	.141	1.805	.071	(-.012;.295)
X2	.208	2.640	.009	(.053;.363)
T	.538	14.581	.000	(.466;.611)
PI	-.181	-4.721	.000	(-.257;-.106)
V	.138	3.680	.000	(.064;.211)
PC	.221	5.508	.000	(.142;.299)
R^2	.599			

Note: If $p < .05$ for either mediating variable, then the b-path depicted in figure 4 is statistically significant. If $p < .05$ for X1 or X2, then the c'-path depicted in figure 4 is statistically significant.

Relative indirect effects of X on Y

Table 15. Relative indirect effect of X on word of mouth

WOM Predictor	Effect	BootSE	95% Boot CI (LL;UL)
X → Trust → WOM			
X1	-.079	.061	(-.197;.039)
X2	-.121	.065	(-.252;.004)
X → Intrusiveness → WOM			
X1	-.050	.027	(-.107;-.001)
X2	-.065	.030	(-.131;-.013)
X → Vulnerability → WOM			
X1	.035	.022	(-.003;.083)
X2	.060	.026	(.016;.118)
X → Privacy → WOM			
X1	-.038	.023	(-.087;.005)
X2	-.082	.028	(-.142;-.032)

Note: If either confidence interval for X1 or X2 does not include zero, then the mediating variable would be mediating.

Table 15 shows that all mediating variables except trust are mediating when it comes to the dependent variable word of mouth. This means that perceived intrusiveness, feelings of vulnerability and privacy concern help explain the effect the independent variable has on the dependent variable word of mouth. More specifically, the test revealed that perceived intrusiveness mediates the relationship between AI-assisted surveillance and wom intention for both X1 ($CI_{95\%}$ = [-.107;-.001]) and X2 ($CI_{95\%}$ = [-.131;-.013]). This means that the mediating effect of perceived intrusiveness is significant when comparing the control group vs moderate degree (X1) and when comparing the control

group vs high degree (X2). The test also revealed that feelings of vulnerability mediates the relationship between AI-assisted surveillance and wom intention for X2 ($CI_{95\%}$ = [.016;.118]). This means that the mediating effect of feelings of vulnerability is significant when comparing the control group vs high degree (X2). However, the indirect effect coefficient in table 15 was positive rather than negative, which is opposite of what was hypothesized. In addition, the test revealed that privacy concerns regarding the store mediates the relationship between AI-assisted surveillance and wom intention for X2 ($CI_{95\%}$ = [-.142;-.032]). This means that the mediating effect of privacy concern is significant when comparing the control group vs high degree (X2). The results partly support H3d and fully support H3b since perceived intrusiveness showed mediation for all dependent variables.

Table 16. Mediation hypothesis

H3a	Any degree of AI-assisted surveillance in self-checkouts will lead to higher feelings of vulnerability, leading to lower behavioral intentions.	Partially supported*
H3b	Any degree of AI-assisted surveillance in self-checkouts will lead to higher perceived intrusiveness, leading to lower behavioral intentions.	Supported
H3c	Any degree of AI-assisted surveillance in self-checkouts will lead to lower trust, leading to lower behavioral intentions.	Rejected
H3d	Any degree of AI-assisted surveillance in self-checkouts will lead to higher privacy concerns, leading to lower behavioral intentions.	Partially supported**

Note: * = H3a is partially supported for RI, see table 13. ** = H3d is partially supported for WOM, see table 15.

When it comes to word of mouth, then all mediating variables except trust mediate the relationship between the independent variable and the dependent variable. However, the effect was opposite than hypothesized for feelings of vulnerability. When revisit intention was tested, perceived intrusiveness and feelings of vulnerability were mediating. Looking at intention to use showed that only perceived intrusiveness mediated the relationship between the independent variable and intention to use. Apart from the significant results, these results indicate that the respondents level of trust for the store does not indicate whether their behavioral intentions will be positive or negative.

4.4. Results for moderated mediation regression analysis (model 8)

For a moderated mediation to have taken place, then the interaction variable in tables 17, 18, and 19 must be significant for either Int_1 or Int_2. If they are not, then a moderated mediation cannot be claimed to have taken place. For full results on PROCESS model 8, see appendix 5 and 6. However, if the interaction term was significant then moderated mediation would have taken place if the 95% confidence interval for index of moderated mediation did not contain zero. All the coefficients in the following tables are also unstandardized coefficients. When looking at tables 17 through 19, X1 and X2, and the mediating predictors can be interpreted in a similar way as tables 10, 12, and 14. The coefficient for the Mod (moderator) predictor shows whether the presence of information disclosure about surveillance changes the dependent variable. A small and non-significant coefficient, such as Mod in table 17, would indicate that merely providing information does not significantly alter how users intend to interact with the self-checkout system. The interaction terms, Int_1 (X1 x Mod) and Int_2 (X2 x Mod), assess whether the effect of AI-assisted surveillance on the dependent variable changes when information is disclosed. Non-significant coefficients for these terms suggest that the influence of AI-assisted surveillance on the dependent variables does not significantly differ with the presence or absence of information disclosure.

4.4.1. Intention to use the self-checkout system

Table 17. PROCESS model 8 outcome variable intention to use

IU Predictor	Coeff	t	p	95% Boot CI (LL;UL)
X1	.226	1.623	.105	(-.047;.498)
X2	.373	2.581	.010	(.089;.657)
T	.401	8.550	.000	(.309;.493)
PI	-.305	-6.233	.000	(-.401;-.209)
V	-.038	-.790	.430	(-.131;.056)
PC	.009	.174	.862	(-.091;.109)
Mod	.168	1.192	.234	(-.108;.444)
Int_1	-.185	-.931	.352	(-.575;.205)
Int_2	-.355	-1.780	.076	(-.746;.037)
R^2	.621			

Note: If $p < .05$ for X1 or X2 then c'1 or c'2 path would be statistically significant. All the mediating variables are for the b-path. Mod is for the c'3 path, and Int_1 and Int_2 are for c'4 and c'5 paths respectively. See figure 4 for paths. For there to be a direct effect of the degree of AI-assisted surveillance on intention to use, then either Int_1 or Int_2 has to be statistically significant.

Since neither Int_1 or Int_2 was statistically significant when testing the dependent variable intention to use, one cannot claim that a moderated mediation has taken place.

Hence, we did not include the material one can use to probe further, these are located in appendix 6.

4.4.2. Revisit intention

Table 18. PROCESS model 8 outcome variable revisit intention

RI Predictor	Coeff	t	p	95% Boot CI (LL;UL)
X1	.101	.974	.330	(-.103;.305)
X2	.148	1.374	.170	(-.064;.360)
T	.386	11.014	.000	(.317;.455)
PI	-.187	-5.119	.000	(-.259;-.115)
V	-.090	-2.523	.012	(-.159;-.020
PC	.075	1.972	.049	(.000;.150)
Mod	.054	.516	.606	(-.152;.260)
Int_1	.034	.226	.821	(-.258;.325)
Int_2	-.048	-.323	.747	(-.340;.244)
R^2	.611			

Note: If $p < .05$ for X1 or X2 then c'1 or c'2 path would be statistically significant. All the mediating variables are for the b-path. Mod is for the c'3 path, and Int_1 and Int_2 are for c'4 and c'5 paths respectively. See figure 4 for paths. For there to be a direct effect of the degree of AI-assisted surveillance on revisit intention, then either Int_1 or Int_2 has to be statistically significant.

In table 18 we can see that neither Int_1 or Int_2 was significant for the dependent variable revisit intention, meaning that one cannot claim that a moderated mediation has taken place. For the full extent of the output for model 8, please see appendix 5 and 6.

4.4.3. Word of mouth

Table 19. PROCESS model 8 outcome variable word of mouth

WOM Predictor	Coeff	t	p	95% Boot CI (LL;UL)
X1	.075	.683	.495	(-.140;.290)
X2	.188	1.647	.100	(-.036;.411)
T	.536	14.512	.000	(.464;.609)
PI	-.178	-4.607	.000	(-.253;-.102)
V	.134	3.581	.000	(.061;.208)
PC	.221	5.520	.000	(.143;.300)
Mod	-.154	-1.387	.166	(-.371;.064)
Int_1	.128	.820	.413	(-.179;.436)
Int_2	.046	.292	.770	(-.262;.354)
R^2	.601			

Note: If $p < .05$ for X1 or X2 then c'1 or c'2 path would be statistically significant. All the mediating variables are for the b-path. Mod is for the c'3 path, and Int_1 and Int_2 are for c'4 and c'5 paths respectively. See figure 4 for paths. For there to be a direct effect of the degree of AI-assisted surveillance on word of mouth, then either Int_1 or Int_2 has to be statistically significant.

Table 19 indicates that Int_1 and Int_2 was not significant which entails that a moderated mediation has not taken place. For full results of the model 8, please see appendix 5 and 6.

Table 20. Moderated mediation hypotheses

H4a	The effect where any degree of AI-assisted surveillance in self-checkouts lead to higher feelings of vulnerability, leading to lower behavioral intentions, will be lessened by the presence of information disclosure (versus no information disclosure).	Rejected
H4b	The effect where any degree of AI-assisted surveillance in self-checkouts lead to higher perceived intrusiveness, leading to lower behavioral intentions, will be lessened by the presence of information disclosure (versus no information disclosure).	Rejected
H4c	The effect where any degree of AI-assisted surveillance in self-checkouts lead to lower trust, leading to lower behavioral intentions, will be lessened by the presence of information disclosure (versus no information disclosure).	Rejected
H4d	The effect where any degree of AI-assisted surveillance in self-checkouts lead to higher privacy concerns, leading to lower behavioral intentions, will be lessened by the presence of information disclosure (versus no information disclosure).	Rejected

Note: The interaction term in tables 17, 18, and 19 must be significant to probe the indirect effect of the moderated mediation. Since none of the interaction terms were significant, all the moderated mediation hypotheses were rejected.

These results indicate that the disclosure of information before being exposed to either of the degrees of AI-assisted surveillance did not have a significant impact on the respondents. Hence, all hypotheses regarding information disclosure (H4a-d) were rejected.

5. Discussion and conclusions

How do customers respond to different degrees of AI-assisted surveillance in grocery store self-checkouts?

To determine how the customers responded to varying degrees of AI-assisted surveillance, a significant ANOVA test is required to solidify the findings. Since none of the ANOVA tests in table 8 were significant regarding the dependent variables, the authors cannot claim that the respondents were less willing to use the self-checkouts as the degree of AI-assisted surveillance increased. Neither their intention to revisit the store or recommend it decreased. However, it was evident that as the degree of AI-assisted surveillance increased, so did respondents' reported feelings of vulnerability, their concerns regarding privacy and the perceived intrusiveness of the experience. These findings proved statistically significant when looking at the ANOVA tests reported in table 8.

Which customer perceptions and emotions help explain their behavioral intentions?

Whether the measured perceptions and emotions help explain the respondents' behavioral intentions come down to if the mediation test was significant which can be gathered by looking at table 16. Perceived intrusiveness proved to be the best explanatory variable since it mediated all three behavioral intentions. Feelings of vulnerability came in second since it helped explain the respondent's intention to revisit and recommend the store, however the effect for the latter was opposite to what was hypothesized. The third best explaining variable was privacy concerns which proved to have a mediating effect when looking at word of mouth. Trust towards the store was surprisingly the worst mediating variable since it did not mediate the relationship for any of the measured behavioral intentions.

Does information disclosure make a difference in how they respond?

Deciding if information disclosure makes a difference in how the respondents reported their experience was investigated with a moderated mediation test. Looking at table 20 shows us that information disclosure failed to moderate the indirect effect on all accounts. Hence, information disclosure does not make a difference in how the respondents' answered the survey and it seems that information disclosure did not help mitigate the response to an increased degree of AI-assisted surveillance.

5.1. Discussion

5.1.1. Behavioral intentions

None of the hypotheses for the ANOVA tests (table 8) regarding the dependent variables came back statistically significant. However, there is still a trend showing that

the mean for high degree of AI-assisted surveillance is worse off than the control group. This most likely entails that there are a few respondents who feel that AI-assisted surveillance is worse, but the majority does not seem to care which is a positive thing for the implementation of AI in grocery stores. Given that there is still an opportunity for this minority to choose a traditional checkout operated by human staff, Swedish grocery stores who implement similar AI-assisted surveillance into their self-checkouts will most likely save more money on prevented theft than they lose on customer churn. For instance, Nilsen (2023) reports how the global Swedish retailer IKEA, who mainly uses self-checkouts at their stores, has begun testing similar AI-assisted solutions in their self-checkouts. IKEA trying out AI-assisted solutions in their self-checkouts proves that there is a genuine interest and use case for AI-assisted solutions in Swedish stores.

The means for customers' behavioral intentions were lowest for the high degree of AI-assisted surveillance, while the moderate degree of AI-assisted surveillance was closer to the control group. This trend is consistent with previous researchers' findings where retail technologies encompassing more elements of AI received lower behavioral intentions than traditional self-checkouts or technologies with fewer AI elements (Inman & Nikolova, 2017; Ponte & Bonazzi, 2023). This suggests that the moderate degree of AI surveillance is a better option, even if the differences were small. For example, if one looks at table 8 and compares the difference between the revisit intention among the control group ($M_{RI, Control} = 5.01$, $SD_{RI, Control} = 1.30$), the moderate degree ($M_{RI, Moderate} = 4.97$, $SD_{RI, Moderate} = 1.26$), and the high degree ($M_{RI, High} = 4.85$, $SD_{RI, High} = 1.36$), one could see that the difference is bigger between the control group and the high degree, than between the control group and the moderate degree. This is interesting since the biggest difference between the moderate and high degree was the video shown to the customers in the high degree scenario. The video was shown on the self-checkout screen which replays recorded footage of a customer performing an unsuccessful scan. This trend could indicate that the disturbing factor for the respondents was the recorded video, not the AI technology. The fact that visible video footage of oneself can impact customers' checkout experience has been documented as grocers and retailers experiment with different technological solutions. Kjellin (2024) writes about an ICA store in Sweden that implemented a CCTV feature by the self-checkouts where the customers see themselves from above while checking out. The customers might find it deterring, and the grocers do not seem able to measure its actual effect. Given our trends and results in this thesis, the case for using AI-assisted surveillance without visible video footage might prove the most effective result. This is not an unreasonable result given that the best possible anti-theft solution is the one that does not deter your non-shoplifting customers but catches the deviant customers effectively.

The notion regarding performing the experiment in store rather than having a scenario in a survey became evident when looking at previous research (Chang & Chen, 2021; Dabholkar et al., 2003; Demirci Orel & Kara, 2014; Fernandes & Pedroso, 2017; Weijters et al., 2007; Wu et al., 2024). There have been opinions that these studies are best performed in person to get the best results (Donovan & Rossiter, 1982). Another approach is studies performing online surveys about specific stores like Amazon Go or BingoBox (Esch et al., 2021; Park & Zhang, 2022; Ponte & Bonazzi, 2023). However, as previously mentioned the thesis would have either been a very costly endeavor or a highly experimental study given that the technology being examined is not available to the authors knowledge in any Swedish grocery store at the time of collecting the data. The fact that our results might have been improved by having actual test stations in store became evident when we did our pre-survey. Some pre-survey participants voiced their opinions about the dependent variable, which at the time of testing was only one variable instead of the final three that made it into the official survey, where one of the items contained a question pertaining to word of mouth. The participants meant that it was odd to recommend a store with little information provided about the store itself. The decision to provide as little information as possible about the store was made to avoid biases since we wanted the respondents to focus on the technology and not the store itself. If the scenario suggested "think about your favorite store", it would not be possible to rule out their preexisting attitude to that particular store. Therefore, we asked them to imagine a new store in their neighborhood. The authors believe better results might have been reached given an in-store collection method, given that it was a feasible option. Nevertheless, the economical barrier on its own and the lack of matching technology was reason enough to not pursue the in-store path.

5.1.2. Emotions and perceptions

The ANOVA tests for all the mediating variables except trust came back significant. Which means that a higher degree of AI-assisted surveillance is linked to an increase in privacy concern (the lower the reported number the more concerned they are for their privacy), an increase in how vulnerable they feel, and an increased perception of intrusiveness. In spite of that, the ANOVA tests did not come back reporting that the degree of AI-assisted surveillance was so high that they did not intend to use it.

To interpret the results from model 4, we mentioned previously that even if there were only one significant mediation shown for either of the two variables X1 or X2, the mediating variable would be considered mediating (Hayes, 2022). Hence, for word of mouth, the variables vulnerability, perceived intrusiveness and privacy concerns were all found to mediate the relationship between the degree of AI-assisted surveillance and word of mouth. Revisit intention was mediated by vulnerability and perceived intrusiveness. Whereas intention to use was mediated by perceived intrusiveness. The fact that these variables mediate the relationship between the degree of AI-assisted

surveillance and customers behavioral intentions are in line with previous studies about online behavioral advertisement, where the same variables were found to mediate the relationship between the degree of personalized advertisement and various behavioral intentions (Aguirre et al., 2015; Bleier & Eisenbeiss, 2015; Miyazaki, 2008; Stanaland et al., 2011; van Doorn & Hoekstra, 2013).

Unfortunately, trust did not mediate the relationship between the independent variable and any of the dependent variables. This insignificant result goes against previous studies from the OBA and AI literature where researchers found that trust towards the advertiser or the store have a mediating effect (Bleier & Eisenbeiss, 2015; Inman & Nikolova, 2017; Sharma et al., 2022; Wu et al., 2024). However, if the test had been carried out in an actual grocery store, the questions relating to the store itself, such as the items for trust, might have been easier for the respondents to answer. As mentioned before, conducting the study in an actual store proved logistically impossible due to several reasons but should be considered in future research. At the same time, it might have been more difficult to ascertain whether the customers trust the store because they like or dislike the brand and already have a relationship with said store.

5.1.3. Transparency

Even if all the hypotheses for transparency were rejected (see table 20), the result still revealed interesting trends. For example, respondents who were given information disclosure and exposed to the self-checkout scenario with no degree of AI had a lower mean for word of mouth intentions ($M_{WOM,\ Control,\ Disclosure} = 4.31$, $SD_{wom,\ Control,\ Disclosure} = 1.37$), than respondents who did not receive information disclosure but were exposed to the same self-checkout scenario with no AI-assisted surveillance ($M_{WOM,\ Control,\ No\ Disclosure} = 4.66$, $SD_{wom,\ Control,\ No\ Disclosure} = 1.30$). Meaning that customers who did not receive information disclosure before using a traditional self-checkout without AI, were more likely to recommend the store to friends. The trend implies that being transparent about theft prevention only makes customers less likely to recommend the store. Intention to use and Revisit intention had similar trends, where the means for information disclosure were slightly lower compared to no information disclosure. Another interesting trend was found for perceived intrusiveness. When customers were not given information disclosure, perceived intrusiveness was almost considered a linear function in relation to the degree of AI-assisted surveillance (see table 7). However, when respondents were given information disclosure, the highest mean for perceived intrusiveness was found for the moderate degree of AI-assisted surveillance. This is interesting since it deviates from the linear function displayed in the means for most other variables.

In general, it seems that respondents who were exposed to the information disclosure reported lower means for behavioral intentions than the respondents who were not exposed to the information disclosure. This trend in means goes against the hypothesis

and previous literature on OBA, that showed increased behavioral intentions when customers are exposed to information disclosure (Aguirre et al., 2015; Miyazaki, 2008; Stanaland et al., 2011). Even if the effect was not significant, it still begs the question whether the partaking of information affects the respondent in a negative way. It is possible that information disclosure just made respondents more aware of and attentive to the theft-prevention presented in the scenario which could have led to a stronger reaction if they disliked it. Another explanation for this interesting trend could be how the sign with information disclosure was formulated in the survey. Since the sign with information disclosure had to work for the control-group as well, information about the AI-assisted surveillance itself was not included. Instead, the sign simply made customers aware that they might be exposed to theft-prevention checks due to increased theft in the store. Looking at the OBA literature, most of the studies included some form of disclosure regarding data collection and how the advertiser or company intended to use the data. Even if the technology used for this experiment did not use facial recognition or collect biometric data, customers might think so if they are not given any information. It is possible that just giving customers a notion of increased theft and theft prevention had a negative effect on the respondents who might think they were targeted or suspected of such activities. The privacy calculus model suggests that customers engage in a calculus when they evaluate the costs versus the benefits of sharing their personal data in certain situations. Consumers are more willing to share personal data if they believe that the benefits outweigh the costs. Based on this theory, one could argue that the information disclosure was seen as a cost since it made the respondents more aware of negative aspects such as increased theft and the fact that they might have to go through a theft prevention check, which could tip the scales in terms of benefits and costs in favor of the cost side.

Given that the solution implemented into the grocery store's system does not invade one's privacy, use the data gathered for malicious purposes, or go against EU regulation regarding surveillance – then it might be better to not disclose information regarding theft prevention in the way it was formulated in this experiment, since it might negatively affect the experience. After all, given that the system works properly, the inconvenience of being caught by the system would only occur if deviant behavior were detected. Meaning that all the customers who behave should not be bothered by the implementation of the new technology.

5.2. Conclusions and implications

From a theoretical standpoint, this thesis empirically validated the Stimulus-Organism-Response model (S-O-R model) in a new setting. The setting was self-checkout areas in grocery stores where customers are exposed to different degrees of the environmental stimuli AI-assisted surveillance. The model was modified by adding new variables that were thought to explain how customers respond to AI-assisted surveillance. Three of the

added variables in the organism, perceived intrusiveness, feelings of vulnerability and privacy concern, were found to mediate the relationship between the stimuli and external response. Hence, this study successfully confirmed the S-O-R models predictions and expected outcomes. Trust towards the store was the only added variable in the organism that was not found to be mediating. Transparency was added as a moderator, but the results were not significant. However, we encourage further exploration of transparency in the context of AI-assisted surveillance, since the insignificant results may only apply to the way information disclosure was formulated and presented in this specific experiment. Since the majority of the added emotions and perceptions effectively mediated the relationship between stimuli and response, we propose that our modification of the S-O-R model could serve as a valuable framework for future research about customer responses to surveillance technologies, offering an alternative to existing technology acceptance theories.

When it comes to practical implications, this thesis provides valuable insights. Given that none of ANOVA tests for the dependent variables were significant, and that the means of the behavioral intentions were not negative, rather positive – one would say that this thesis found nothing that evidently speaks against implementing AI-assisted surveillance technology in self-checkouts in Swedish grocery stores. Furthermore, there is nothing in the data that would suggest that Swedish grocery stores would lose customers based on the decision of implementing the system, however, there are no significant discoveries proving the opposite either. Merely looking at the trends and means of the behavioral intentions the authors conclude that the Swedish population uses self-checkouts to quite a large extent and it is not too bothered with using self-checkouts assisted by artificial intelligence. At least when they are not shown a video of the encounter. Since the intention was to examine whether implementing AI surveillance in self-checkouts produced any negative reactions or risks, the lack of significant results can be considered joyous news for Swedish retailers interested in implementing cutting edge AI technology in their self-checkouts. This since Swedish customers do not really seem to care whether they are monitored by AI in a self-checkout or not. At least not to a statistically significant degree.

Looking at the results one can see that the high degree of AI assisted surveillance seems to create more negative feelings than the moderate degree. Hence, the moderate degree without on-screen video recording being shown to the customers seems like the best solution for the Swedish market.

To answer the initial question posed in the introduction of the thesis, the authors cannot claim whether the AI-assisted surveillance software can effectively save grocers millions of dollars. But they can assure them that the Swedish population would not mind finding out.

5.3. Limitations and suggestions for further research

5.3.1. Limitations and criticisms

As previously discussed, the authors did not deem it feasible to conduct the research in a physical grocery store due to the technology not being available, lack of participating stores and the issues that might arise regarding behavioral intentions concerning the loyalty domain. Regardless, the results could have differed, especially for trust, privacy concern, revisit intention and wom intention, since these questions pertained particularly to the store, if it had been conducted in a physical grocery store which would be worth looking into.

Another limitation that could have had an impact on the results were the fact that using the OBA literature meant equaling degree of personalization of ads to degree of AI-assisted surveillance. Even if the results for most of the mediating variables were in line with the OBA literature, the results for information disclosure were not. If the subject were to be investigated further in future research, this notion might need to be handled in a different way. The authors believe the key difference is the fact that information disclosure was necessary in the OBA literature since the ads were personalized based off collected individual data, whereas the AI-assisted surveillance technology used in this thesis would not collect or store any identifying data of the customers.

A possible mitigation of the risks associated with conducting the study in a survey with scenarios-based form was the larger sample the authors were able to collect thanks to Norstat. However, one possible criticism is that the instruction manipulation check only screened 0.1% of the participants which can be seen as a small number. This could have been due to the IMC being too simple, or the fact that the Norstat sample holds a very high quality, or that our survey was short enough to not endanger the attention span of the respondent. Nevertheless, the low screening rate of the IMC can be seen as an anomaly or an attentive recorded sample.

At the moment of sending out the survey we intended to investigate attitude first as a dependent variable, then we opted for mediating variable. But after discussion and due to the known relationship between behavioral intention and attitude it seemed both complicated and unnecessary to account for attitude in an already complicated moderated mediation model. It did not show any significant results in testing and there was not a noticeable difference when removing it from the tests. Hence, we opted to remove it.

5.3.2. Future research

The thesis was focused on grocery stores since the societal debate was centered around this issue and the authors needed to delimit the study. Hence, a suggestion for future research would be to try out the effect of AI integration in different areas. For instance,

the Swedish government monopoly selling alcohol in Sweden, Systembolaget, has recently started using self-checkouts. Given the age restriction of 20 years minimum, and the lack of other options in terms of places that are legally able to sell alcohol might prove for interesting insights into brand loyalty.

In addition to try out the effect in different contexts, we propose that a similar study is conducted in-store where the respondents are exposed to the AI-assisted surveillance in real life and not just through a scenario. By conducting the study in a store, one could rule out potential misunderstandings about how the technology works and the respondents would have a better chance of shaping their opinion about whether they trust the store and want to return.

This study did not include a sign that disclosed the use of artificial intelligence since the control group was not exposed to AI-assisted surveillance. Therefore, a suggestion for future research could be regarding information disclosure where customers are informed that the AI-assisted surveillance does not collect or use any biometric data. Another research suggestion on the same topic could be to explore technologies such as Facewatch which do collect biometric data with facial recognition. Given that the OBA literature regarding information disclosure showed good results when information was disclosed when personal data was collected and handled, then a more similar scenario such as the collection and storage of biometric data might be more applicable.

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7. Appendices

Appendix 1 – The distributed survey (Swedish)

Start of Block: Introduction

Kära deltagare.

Vi är två masterstudenter från Handelshögskolan i Stockholm. Just nu skriver vi vår masteruppsats där vi undersöker självutcheckningskassor i mataffärer. Du kommer först få läsa ett scenario och sedan svara på några frågor om självutcheckning. Var god läs igenom scenariot noggrant innan du börjar svara på frågorna.

Enkäten tar ungefär 7 minuter att besvara. Svaren är helt anonyma och kommer behandlas konfidentiellt. Vänligen läs igenom GDPR informationen nedan och bekräfta att du tagit del av informationen.

Frågor? Om du har några frågor angående enkäten eller uppsatsen så kan ni kontakta oss på:
24424@student.hhs.se
24184@student.hhs.se

GDPR Consent to participation in student's survey.
The student's project. As an integral part of the educational program at the Stockholm School of Economics, enrolled students complete an individual thesis. This work is sometimes based upon surveys connected to the subject. Participation is naturally entirely voluntary, and this text is intended to provide you with the necessary information that may concern your participation in the study or interview. You can at any time withdraw your consent and your data will thereafter be permanently erased.

Confidentiality. Anything you say or state in the survey will be held strictly confidential and will only be made available to supervisors, tutors, and the course management team.
Secured storage of data. All data will be stored and processed safely by the SSE and will be permanently deleted when the project is completed.
No personal data will be published. The thesis written by the students will not contain any information that may identify you as a participant in the survey subject.
Your rights under GDPR. You are welcome to visit https://www.hhs.se/en/about-us/contact/data-protection/ in order to read more and obtain information on your rights related to personal data.

Jag har tagit del av GDPR-informationen ovan och samtycker till att delta i denna studien.

- ○ Ja (1)
- ○ Nej tack, jag samtycker inte till att delta i studien. (Enkäten avslutas) (2)

End of Block: Introduction

Start of Block: 1. Scenario Introduction

Scenario: Föreställ dig att du går in i en ny mataffär som precis har öppnat i ditt område. Du tar några varor och går till kassorna. Du ser att de har vanliga kassor (dvs. med en anställd som sköter kassan) och självutcheckningskassor (dvs. där du själv scannar dina varor). Du väljer självutcheckning och precis när du är på väg till området med självutcheckningskassor ser du en skylt som säger följande:

End of Block: 1. Scenario Introduction

Start of Block: 1.1. With Disclosure (Moderator = 1)

På skylten står följande: "Välkommen till vår självutcheckning. Vi har utsatts för stölder i butiken och har därför infört extra åtgärder för att förhindra detta. Detta innebär att vi har kontroller vid självutcheckningskassorna. Tack för att du handlar hos oss, vi hoppas att du får en trevlig upplevelse."

End of Block: 1.1. With Disclosure (Moderator = 1)

Start of Block: 1.2. Without Disclosure (Moderator = 0)

På skylten står följande: "Välkommen till vår självutcheckning. Tack för att du handlar hos oss, vi hoppas att du får en trevlig upplevelse."

End of Block: 1.2. Without Disclosure (Moderator = 0)

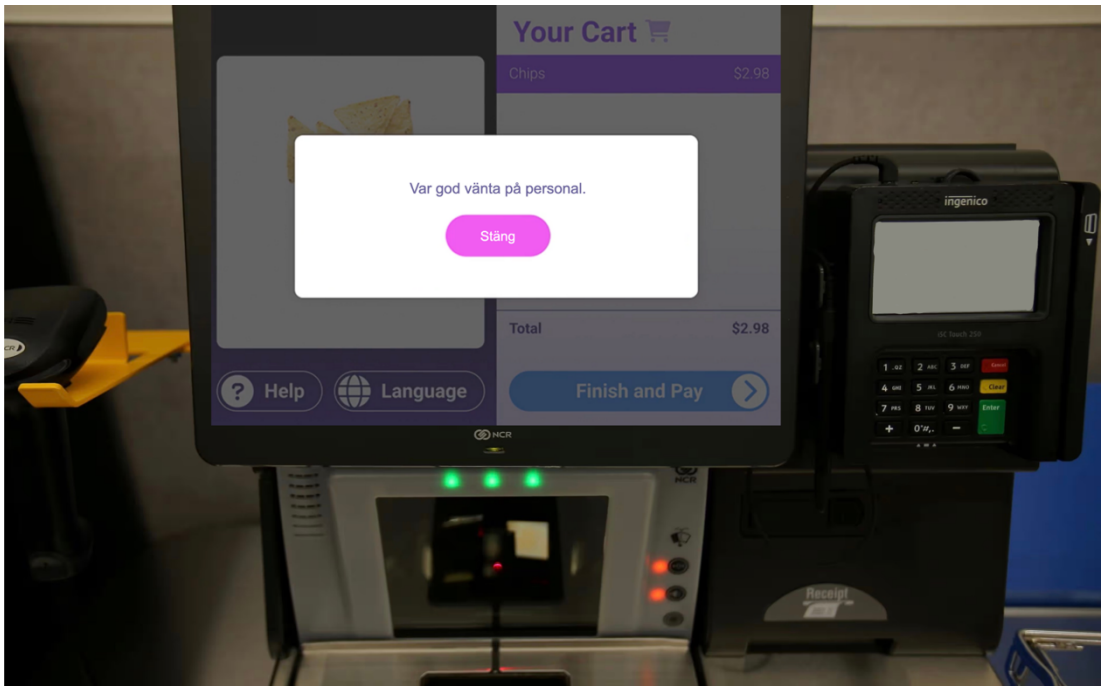
Start of Block: 2. Scenario

Du plockar upp din korg och går till en självutcheckningskassa för att betala. Du skannar dina varor och lägger dem i din påse. När du har lagt den sista varan i påsen visas plötsligt ett meddelande på skärmen:

End of Block: 2. Scenario

Start of Block: 2.1. Computer vision – video (X = 3)

Meddelandet på skärmen lyder: "Var god vänta på personal."



AI-systemet som implementerats i självutcheckningskassan har påkallat personal. Kort därefter kommer en anställd till din självutcheckningskassa och scannar sitt kort. Var god kolla på videon nedan för att se vad som händer.



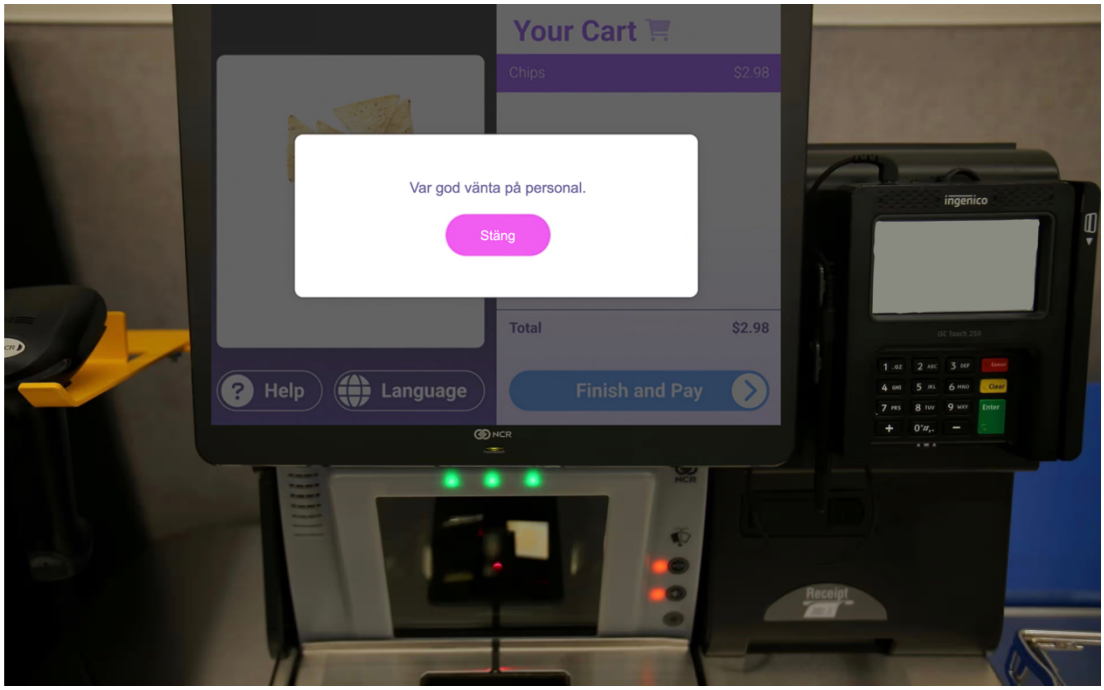
Här är en beskrivning av vad som sker i videon:

På skärmen ser du en video av dig själv, filmad ovanifrån med övervakningskameror i taket. Den anställda granskar videon på dig när du scannade dina varor och ser att du inte lyckades scanna den sista varan. Den anställde scannar varan åt dig och låter dig sedan fortsätta.

End of Block: 2.1. Computer vision – video (X = 3)

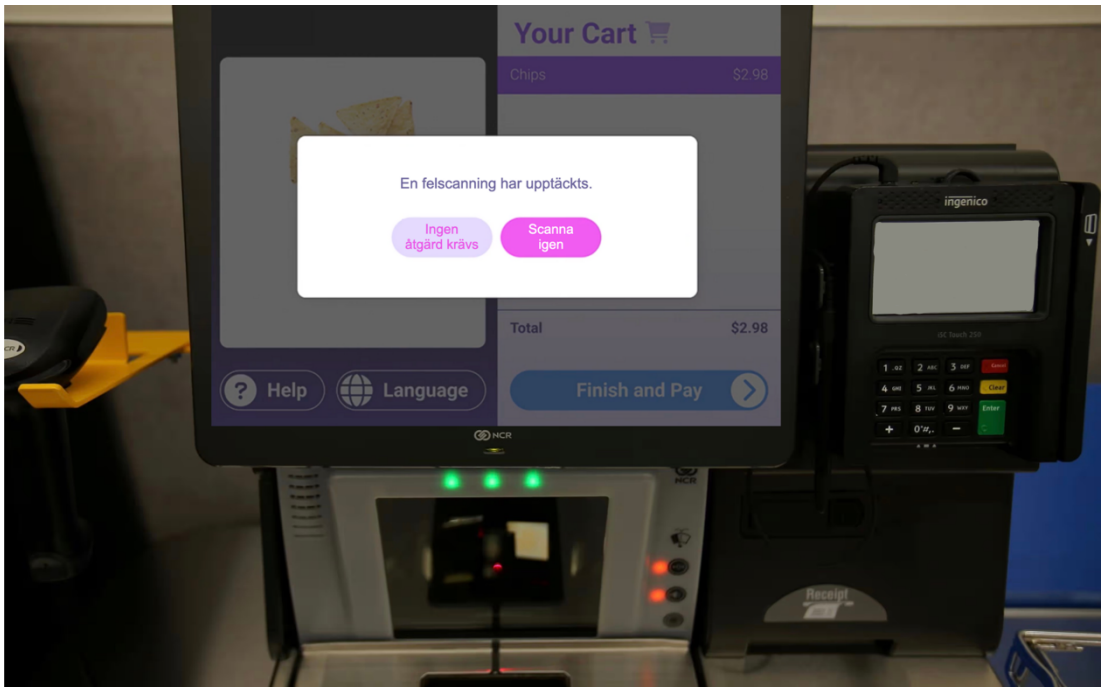
Start of Block: 2.2. Computer vision - no video (X = 2)

Meddelandet på skärmen lyder: "Var god vänta på personal."



AI-systemet som implementerats i självutcheckningskassan har påkallat personal. Kort därefter kommer en anställd till din självutcheckningskassa och scannar sitt kort. Ett nytt meddelande dyker upp på skärmen:

Meddelandet på skärmen lyder: "En felscanning har upptäckts."

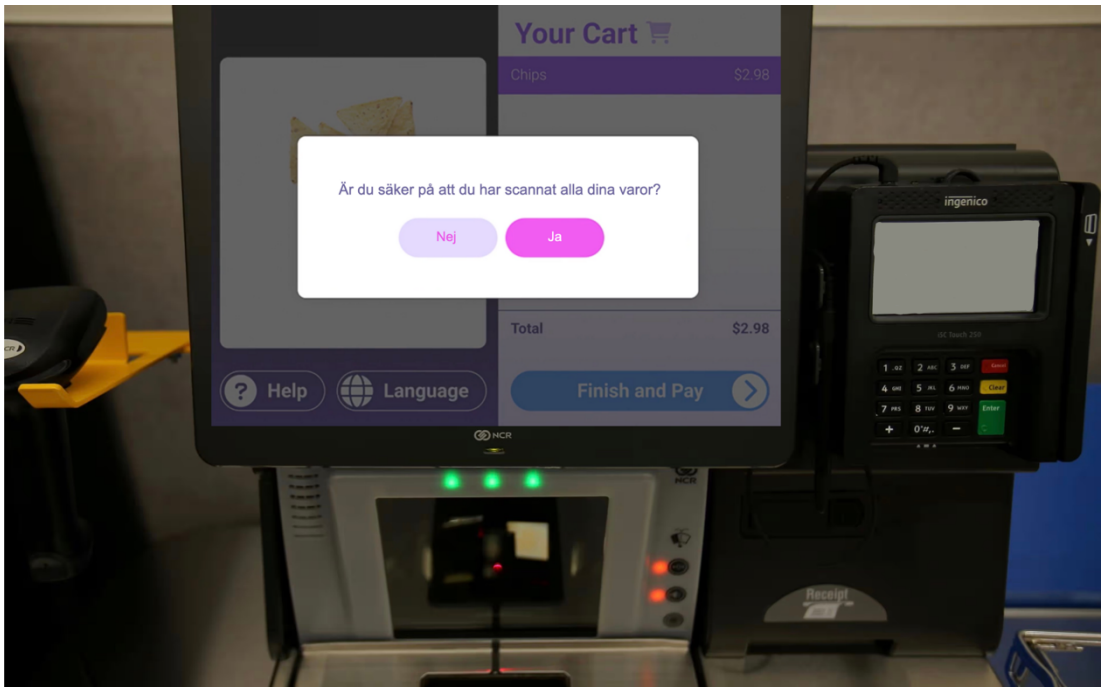


Den anställda informerar dig om att det nya AI-systemet upptäckt att din sista vara inte scannades ordentligt. De scannar din vara åt dig och låter dig fortsätta.

End of Block: 2.2. Computer vision - no video (X = 2)

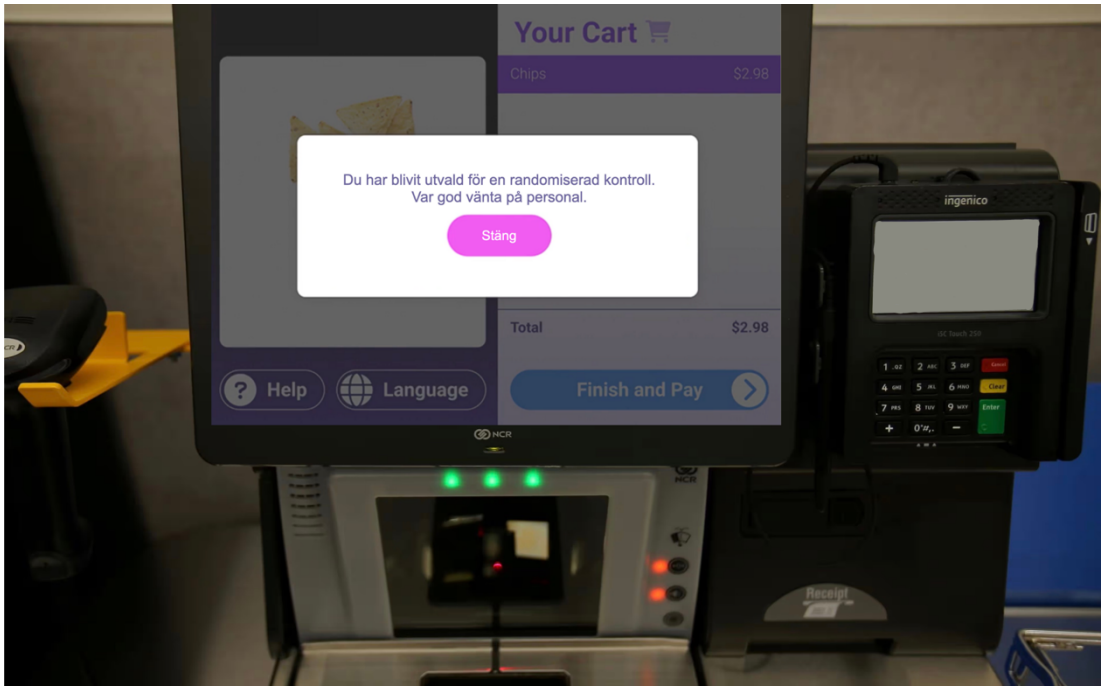
Start of Block: 2.3. standard random check (X = 1)

Meddelandet på skärmen lyder: "Är du säker på att du har skannat alla dina varor?"



Du trycker på "Ja" och ett nytt meddelande dyker upp på skärmen.

Meddelandet på skärmen lyder: ”Du har blivit utvald för en randomiserad kontroll. Var god vänta på personal.”



Kort därefter kommer en anställd till din självutcheckningskassa. Den anställda scannar dina varor och märker att du inte lyckades scanna din sista vara. De scannar varan åt dig och låter dig fortsätta.

End of Block: 2.3. standard random check (X = 1)

Start of Block: 3. Self-checkout experience / kontrollfråga

Hur ofta använder du självutcheckningsalternativet i mataffärer?

- ○ Inte alls (1)
- ○ Mindre än en gång i veckan (2)
- ○ Ungefär en gång i veckan (3)
- ○ 2 eller 3 gånger i veckan (4)
- ○ 4 till 6 gånger i veckan (5)
- ○ Ungefär en gång om dagen (6)
- ○ Mer än en gång om dagen (7)

End of Block: 3. Self-checkout experience / kontrollfråga

Start of Block: 4. Attitude + Dependent Variables

I vilken utsträckning håller du med om följande påståenden om självutcheckningssystemet och mataffären som beskrivs i scenariot?

	Instämmer inte alls (1)	Instämmer inte (2)	Instämmer till viss del inte (3)	Varken instämmer eller instämmer inte (4)	Instämmer till viss del (5)	Instämmer (6)	Instämmer helt (7)
Att handla varor via detta självutcheckningssystem skulle kännas bra (1)	○	○	○	○	○	○	○
Att handla varor via detta självutcheckningssystem skulle kännas givande (2)	○	○	○	○	○	○	○
Att handla varor via detta självutcheckningssystem skulle kännas trevligt (3)	○	○	○	○	○	○	○
Förutsatt att jag har tillgång till detta självutcheckningssystem, är min avsikt att använda det (4)	○	○	○	○	○	○	○
Förutsatt att jag har tillgång till detta självutcheckningssystem, skulle jag använda det (5)	○	○	○	○	○	○	○
Förutsatt att jag har tillgång till detta självutcheckningssystem, förutspår jag att jag skulle använda det (6)	○	○	○	○	○	○	○
Om jag har möjligheten, skulle jag gärna återvända till denna mataffär i framtiden (7)	○	○	○	○	○	○	○

Så länge denna mataffär erbjuder samma nivå av service som under detta besök, skulle jag föredra denna mataffär framför andra (8)	○	○	○	○	○	○	○
Jag skulle inte besöka denna mataffär i framtiden (9)	○	○	○	○	○	○	○
Jag skulle rekommendera denna mataffär till mina vänner (10)	○	○	○	○	○	○	○
Om mina vänner letade efter en bra mataffär, skulle jag tipsa de om denna (11)	○	○	○	○	○	○	○
Det är sannolikt att jag skulle tala gott om denna mataffär med andra (12)	○	○	○	○	○	○	○

End of Block: 4. Dependent Variables

Start of Block: 5. Control Question

Här kommer en fråga för att testa din uppmärksamhet. Markera siffran 4 nedan.

- ○ 1 (1)
- ○ 4 (2)
- ○ 85 (3)
- ○ 27 (4)

End of Block: 5. Control Question

Start of Block: 6. Mediating Variables

I vilken utsträckning håller du med om följande påståenden om självutcheckningssystemet och mattaffären som beskrivs i scenariot?

	Instämmer inte alls (1)	Instämmer inte (2)	Instämmer till viss del inte (3)	Varken instämmer eller instämmer inte (4)	Instämmer till viss del (5)	Instämmer (6)	Instämmer helt (7)
Jag känner att den här mataffären har rutiner som visar att den värdesätter mig som kund (1)	○	○	○	○	○	○	○
Jag känner att denna mataffär har rutiner som visar att den respekterar mig som kund (2)	○	○	○	○	○	○	○
Jag känner att jag kan lita på att den här mataffären är ärlig (3)	○	○	○	○	○	○	○
Det här självutcheckningssystemet är störande (4)	○	○	○	○	○	○	○
Det här självutcheckningssystemet är påträngande (5)	○	○	○	○	○	○	○
Det här självutcheckningssystemet är ovälkommet (6)	○	○	○	○	○	○	○
Det här självutcheckningssystemet får mig att känna mig utsatt (7)	○	○	○	○	○	○	○
Det här självutcheckningssystemet	○	○	○	○	○	○	○

får mig att känna mig oskyddad (8)							
Det här självutcheckningssystemet får mig att känna mig sårbar (9)	○	○	○	○	○	○	○
Jag känner att den här mataffären tar konsumenternas integritet på allvar (10)	○	○	○	○	○	○	○
Jag känner att det är troligt att den här mataffären kommer behandla konsumenterna rättvist när det gäller integritetsfrågor (11)	○	○	○	○	○	○	○
Jag känner att det är troligt att den här mataffären kommer bryta mot integritetsnormer (12)	○	○	○	○	○	○	○

End of Block: 6. Mediating Variables

Start of Block: 7. Consumer Characteristics

Ålder - Hur gammal är du?

- 18 - 24 (2)
- 25 - 34 (3)
- 35 - 44 (4)
- 45 - 54 (5)
- 55 - 64 (6)
- 65 - 74 (7)
- 75 - 84 (8)
- 85 eller äldre (9)

Kön

- Man (1)
- Kvinna (2)
- Icke-binär / tredje kön (3)
- Föredrar att inte ange (4)

Utbildning - Vilken är den högsta utbildningsnivå du har avslutat?

- Mindre än gymnasieexamen (1)
- Gymnasieexamen (2)
- Kandidatexamen (3)
- Masterexamen (4)
- Doktorsexamen (5)
- Yrkesexamen (6)

End of Block: 7. Consumer Characteristics

Note: The survey depicted is in Swedish. The last section called Consumer Characteristics consisted of dropdown menus but were transformed into lists for viewing purposes in this appendix. The video in section 2.1. was borrowed from one of Everseen's instructional videos.

Appendix 2 – The respondents frequency/experience of self-checkouts

Table 21. The respondents frequency/experience of self-checkouts.

Survey N = 743	No information Disclosure (n = 369)		With Information Disclosure (n = 374)		Total (n = 743)	
Variable	n	100%	n	100%	n	100%
Don't use self-checkouts	43	11.7%	51	13.6%	94	12.7%
Use self-checkouts	326	88.3%	323	86.4%	649	87.3%

Note: 369 respondents were not exposed to a disclosure and 374 respondents were exposed to a disclosure statement regarding the technology. In total, after screening procedures, we had 743 respondents.

Appendix 3 – PROCESS model 4 tables for mediators as outcome variables

Table 22. PROCESS model 4 outcome variable trust

Trust				
Predictor	Coeff	t	p	95% Boot CI (LL;UL)
constant	3.737	14.561	.000	(3.233;4.241)
X1	-.146	-1.266	.206	(-.373;.081)
X2	-.224	-1.936	.053	(-.451;.003)
Age	.069	2.587	.010	(.017;.121)
Gender	.122	1.353	.177	(-.055;.300)
Education	-.055	-1.566	.118	(-.124;.014)
Frequency	.299	8.088	.000	(.226;.371)
R^2	.092			

Note: If $p < .05$ for X1 or X2, then the a-path depicted in figure 4 is statistically significant.

Table 23. PROCESS model 4 outcome variable perceived intrusiveness

Intrusiveness Predictor	Coeff	t	p	95% Boot CI (LL;UL)
constant	4.631	14.811	.000	(4.017;5.245)
X1	.275	1.959	.051	(-.001;.552)
X2	.361	2.560	.011	(.084;.637)
Age	-.181	-5.585	.000	(-.245;-.118)
Gender	-.113	-1.024	.306	(-.329;.103)
Education	.044	1.039	.299	(-.039;.128)
Frequency	-.299	-6.644	.000	(-.387;-.211)
R^2	.086			

Note: If $p < .05$ for X1 or X2, then the a-path depicted in figure 4 is statistically significant.

Table 24. PROCESS model 4 outcome variable vulnerability

Vulnerability Predictor	Coeff	t	p	95% Boot CI (LL;UL)
constant	3.526	11.082	.000	(2.901;4.151)
X1	.253	1.769	.077	(-.028;.534)
X2	.439	3.062	.002	(.158;.720)
Age	-.070	-2.116	.035	(-.135;-.005)
Gender	-.004	-.036	.971	(-.224;.216)
Education	.054	1.248	.213	(-.031;.139)
Frequency	-.242	-5.274	.000	(-.331;-.152)
R^2	.052			

Note: If $p < .05$ for X1 or X2, then the a-path depicted in figure 4 is statistically significant.

Table 25. PROCESS model 4 outcome variable privacy concern

Privacy Predictor	Coeff	t	p	95% Boot CI (LL;UL)
constant	3.967	17.084	.000	(3.511;4.423)
X1	-.172	-1.649	.100	(-.377;.033)
X2	-.373	-3.568	.000	(-.579;-.168)
Age	.099	4.096	.000	(.051;.146)
Gender	.009	.107	.915	(-.152;.169)
Education	-.059	-1.872	.062	(-.121;.003)
Frequency	.174	5.211	.000	(.109;.240)
R^2	.066			

Note: If $p < .05$ for X1 or X2, then the a-path depicted in figure 4 is statistically significant.

Appendix 4 – PROCESS model 4 detailed tables for dependent variables as outcome variables

Table 26. PROCESS model 4 outcome variable intention to use

IU Predictor	Coeff	t	p	95% Boot CI (LL;UL)
constant	2.330	5.991	.000	(1.567;3.094)
X1	.132	1.327	.185	(-.063;.327)
X2	.188	1.871	.062	(-.009;.384)
Trust	.402	8.585	.000	(.310;.494)
Intrusiveness	-.299	-6.142	.000	(-.395;-.204)
Vulnerability	-.042	-.877	.381	(-.135;.052)
Privacy	.009	.183	.855	(-.091;.109)
Age	-.054	-2.274	.023	(-.101;-.007)
Gender	.050	.643	.521	(-.103;.203)
Education	.003	.104	.918	(-.056;.062)
Frequency	.560	16.875	.000	(.495;.625)
R^2	.620			

Note: If $p < .05$ for either mediating variable, then the b-path depicted in figure 4 is statistically significant. If $p < .05$ for X1 or X2, then the c'-path depicted in figure 4 is statistically significant.

Table 27: Relative indirect effect of X on intention to use

IU Predictor	Effect	BootSE	95% Boot CI (LL;UL)
X → Trust → IU			
X1	-.059	.046	(-.153;.028)
X2	-.090	.053	(-.202;.004)
X → Intrusiveness → IU			
X1	-.082	.043	(-.173;-.005)
X2	-.108	.049	(-.214;-.021)
X → Vulnerability → IU			
X1	-.011	.017	(-.051;.015)
X2	-.018	.025	(-.074;.026)
X → Privacy → IU			
X1	-.002	.001	(-.023;.020)
X2	-.004	.020	(-.042;.037)

Note: If either confidence interval for X1 or X2 does not include zero, then the mediating variable would be mediating.

Table 28. PROCESS model 4 outcome variable revisit intention

RI Predictor	Coeff	t	p	95% Boot CI (LL;UL)
constant	3.104	10.704	.000	(2.534;3.673)
X1	.114	1.546	.123	(-.031;.260)
X2	.124	1.657	.098	(-.023;.270)
Trust	.387	11.067	.000	(.318;.455)
Intrusiveness	-.184	-5.070	.000	(-.255;-.113)
Vulnerability	-.091	-2.566	.011	(-.160;-.021)
Privacy	.076	2.004	.045	(.002;.150)
Age	-.041	-2.299	.022	(-.076;-.006)
Gender	.033	.570	.569	(-.081;.147)
Education	-.020	-.898	.369	(-.064;.024)
Frequency	.174	7.017	.000	(.125;.222)
R^2	.611			

Note: If $p < .05$ for either mediating variable, then the b-path depicted in figure 4 is statistically significant. If $p < .05$ for X1 or X2, then the c'-path depicted in figure 4 is statistically significant.

Table 29: Relative indirect effect of X on revisit intention

RI Predictor	Effect	BootSE	95% Boot CI (LL;UL)
X → Trust → RI			
X1	-.057	.044	(-.141;.030)
X2	-.087	.048	(-.185;.005)
X → Intrusiveness → RI			
X1	-.051	.027	(-.108;-.002)
X2	-.066	.030	(-.130;-.016)
X → Vulnerability → RI			
X1	-.023	.016	(-.059;.002)
X2	-.040	.021	(-.085;-.006)
X → Privacy → RI			
X1	-.013	.011	(-.039;.003)
X2	-.028	.017	(-.067;.001)

Note: If either confidence interval for X1 or X2 does not include zero, then the mediating variable would be mediating.

Table 30. PROCESS model 4 outcome variable word of mouth

WOM Predictor	Coeff	t	p	95% Boot CI (LL;UL)
constant	.747	2.437	.015	(.145;1.348)
X1	.141	1.805	.071	(-.012;.295)
X2	.208	2.640	.009	(.053;.363)
Trust	.538	14.581	.000	(.466;.611)
Intrusiveness	-.181	-4.721	.000	(-.257;-.106)
Vulnerability	.138	3.680	.000	(.064;.211)
Privacy	.221	5.508	.000	(.142;.299)
Age	-.048	-2.546	.011	(-.084;-.011)
Gender	.069	1.130	.259	(-.051;.190)
Education	-.055	-2.331	.020	(-.102;-.009)
Frequency	.128	4.897	.000	(.077;.179)
R^2	.599			

Note: If $p < .05$ for either mediating variable, then the b-path depicted in figure 4 is statistically significant. If $p < .05$ for X1 or X2, then the c'-path depicted in figure 4 is statistically significant.

Table 31: Relative indirect effect of X on word of mouth

WOM Predictor	Effect	BootSE	95% Boot CI (LL;UL)
X → Trust → WOM			
X1	-.079	.061	(-.197;.039)
X2	-.121	.065	(-.252;.004)
X → Intrusiveness → WOM			
X1	-.050	.027	(-.107;-.001)
X2	-.065	.030	(-.131;-.013)
X → Vulnerability → WOM			
X1	.035	.022	(-.003;.083)
X2	.060	.026	(.016;.118)
X → Privacy → WOM			
X1	-.038	.023	(-.087;.005)
X2	-.082	.028	(-.142;-.032)

Note: If either confidence interval for X1 or X2 does not include zero, then the mediating variable would be mediating.

Appendix 5 – PROCESS model 8 tables for mediators as outcome variables

Table 32. PROCESS model 8 outcome variable trust

Trust Predictor	Coeff	t	p	95% Boot CI (LL;UL)
constant	3.792	13.853	.000	(3.255;4.330)
X1	-.269	-1.661	.097	(-.586;.049)
X2	-.225	-1.338	.181	(-.554;.105)
Mod	-.133	-.811	.418	(-.454;.189)
Int_1	.250	1.080	.281	(-.204;.704)
Int_2	.008	.036	.972	(-.447;.464)
Age	.070	2.626	.009	(.018;.123)
Gender	.126	1.388	.166	(-.052;.304)
Education	-.055	-1.568	.117	(-.124;.014)
Frequency	.299	8.081	.000	(.227;.372)
R^2	.094			

Note: If $p < .05$ for X1 or X2 then a1 or a2 path would be statistically significant. Mod is for the a3 path, and Int_1 and Int_2 are for a4 and a5 paths respectively. See figure 4.

Table 33. PROCESS model 8 outcome variable perceived intrusiveness

Intrusiveness Predictor	Coeff	t	p	95% Boot CI (LL;UL)
constant	4.463	13.391	.000	(3.809;5.118)
X1	.316	1.604	.109	(-.071;.702)
X2	.514	2.518	.012	(.113;.916)
Mod	.254	1.275	.203	(-.137;.645)
Int_1	-.065	-.230	.819	(-.618;.489)
Int_2	-.298	-1.055	.292	(-.853;.257)
Age	-.178	-5.478	.000	(-.242;-.114)
Gender	-.100	-.909	.364	(-.317;.116)
Education	.043	1.002	.317	(-.041;.126)
Frequency	-.295	-6.543	.000	(-.384;-.207)
R^2	.089			

Note: If $p < .05$ for X1 or X2 then a1 or a2 path would be statistically significant. Mod is for the a3 path, and Int_1 and Int_2 are for a4 and a5 paths respectively. See figure 4.

Table 34. PROCESS model 8 outcome variable vulnerability

Vulnerability Predictor	Coeff	t	p	95% Boot CI (LL;UL)
constant	3.512	10.337	.000	(2.845;4.179)
X1	.201	1.000	.318	(-.193;.594)
X2	.442	2.121	.034	(.033;.850)
Mod	.002	.008	.994	(-.397;.400)
Int_1	.112	.391	.696	(-.452;.676)
Int_2	-.005	-.016	.987	(-.570;.561)
Age	-.069	-2.065	.039	(-.134;-.003)
Gender	-.000	-.002	.998	(-.221;.221)
Education	.054	1.242	.215	(-.031;.139)
Frequency	-.241	-5.235	.000	(-.331;-.150)
R^2	.053			

Note: If $p < .05$ for X1 or X2 then a1 or a2 path would be statistically significant. Mod is for the a3 path, and Int_1 and Int_2 are for a4 and a5 paths respectively. See figure 4.

Table 35. PROCESS model 8 outcome variable privacy concern

Privacy Predictor	Coeff	t	p	95% Boot CI (LL;UL)
constant	3.979	16.055	.000	(3.493;4.466)
X1	-.245	-1.671	.095	(-.532;.043)
X2	-.366	-2.409	.016	(-.664;-.068)
Mod	-.048	-.323	.747	(-.339;.243)
Int_1	.150	.718	.473	(-.261;.562)
Int_2	-.011	-.052	.959	(-.423;.402)
Age	.100	4.128	.000	(.052;.147)
Gender	.012	.149	.881	(-.149;.174)
Education	-.059	-1.874	.061	(-.122;.003)
Frequency	.175	5.216	.000	(.109;.241)
R^2	.067			

Note: If $p < .05$ for X1 or X2 then a1 or a2 path would be statistically significant. Mod is for the a3 path, and Int_1 and Int_2 are for a4 and a5 paths respectively. See figure 4.

Appendix 6 – PROCESS model 8 detailed tables for dependent variables as outcome variables

Table 36. PROCESS model 8 outcome variable intention to use

IU Predictor	Coeff	t	p	95% Boot CI (LL;UL)
constant	2.247	5.674	.000	(1.470;3.025)
X1	.226	1.623	.105	(-.047;.498)
X2	.373	2.581	.010	(.089;.657)
Trust	.401	8.550	.000	(.309;.493)
Intrusiveness	-.305	-6.233	.000	(-.401;-.209)
Vulnerability	-.038	-.790	.430	(-.131;.056)
Privacy	.009	.174	.862	(-.091;.109)
Mod	.168	1.192	.234	(-.108;.444)
Int_1	-.185	-.931	.352	(-.575;.205)
Int_2	-.355	-1.780	.076	(-.746;.037)
Age	-.054	-2.272	.023	(-.101;-.007)
Gender	.056	.722	.471	(-.097;.209)
Education	.001	.048	.962	(-.058;.061)
Frequency	.562	16.918	.000	(.497;.627)
R^2	.621			

Note: If $p < .05$ for X1 or X2 then c'1 or c'2 path would be statistically significant. All the mediating variables are for the b-path. Mod is for the c'3 path, and Int_1 and Int_2 are for c'4 and c'5 paths respectively. For there to be a direct effect of the degree of AI surveillance on intention to use, then either Int_1 or Int_2 has to be statistically significant. See figure 4.

Table 37. Relative conditional direct effects of X on intention to use

IU Predictor	Moderator	Effect	t	p	95% Boot CI (LL;UL)
X1	0	.226	1.623	.105	(-.047;.498)
X1	1	.041	.285	.776	(-.239;.320)
X2	0	.373	2.581	.010	(.089;.657)
X2	1	.019	.134	.894	(-.253;.290)

Note: If $p < .05$ for X then it is statistically significant, and the moderator has a moderating effect for the direct path.

Table 38. Indices of moderated mediation intention to use

X → Mediator → IU			
Predictor	Index	BootSE	95% Boot CI (LL;UL)
X → Trust → IU			
X1	.100	.091	(-.070;.290)
X2	.003	.098	(-.197;.189)
X → Intrusiveness → IU			
X1	.020	.084	(-.151;.189)
X2	.091	.091	(-.087;.274)
X → Vulnerability → IU			
X1	-.004	.019	(-.051;.032)
X2	.000	.018	(-.043;.037)
X → Privacy → IU			
X1	.001	.012	(-.023;.030)
X2	-.000	.011	(-.024;.023)

Note: If the confidence interval does not include zero for either the respective X1 or X2 variable, then one can state that there is proof of moderated mediation for that mediating variable. None of the variables in this table are statistically significant.

Table 39. PROCESS model 8 outcome variable revisit intention

RI				
Predictor	Coeff	t	p	95% Boot CI (LL;UL)
constant	3.079	10.414	.000	(2.499;3.660)
X1	.101	.974	.330	(-.103;.305)
X2	.148	1.374	.170	(-.064;.360)
Trust	.386	11.014	.000	(.317;.455)
Intrusiveness	-.187	-5.119	.000	(-.259;-.115)
Vulnerability	-.090	-2.523	.012	(-.159;-.020
Privacy	.075	1.972	.049	(.000;.150)
Moderato	.054	.516	.606	(-.152;.260)
Int_1	.034	.226	.821	(-.258;.325)
Int_2	-.048	-.323	.747	(-.340;.244)
Age	-.040	-2.243	.025	(-.075;-.005)
Gender	.037	.629	.529	(-.078;.151)
Education	-.021	-.912	.362	(-.065;.024)
Frequency	.175	7.037	.000	(.126;.223)
R^2	.611			

Note: If $p < .05$ for X1 or X2 then c'1 or c'2 path would be statistically significant. All the mediating variables are for the b-path. Mod is for the c'3 path, and Int_1 and Int_2 are for c'4 and c'5 paths respectively. For there to be a direct effect of the degree of AI surveillance on revisit intention, then either Int_1 or Int_2 has to be statistically significant. See figure 4.

Table 40. Relative conditional direct effects of X on revisit intention

RI Predictor	Moderator	Effect	t	p	95% Boot CI (LL;UL)
X1	0	.101	.974	.330	(-.103;.305)
X1	1	.135	1.269	.205	(-.074;.343)
X2	0	.148	1.374	.170	(-.064;.360)
X2	1	.100	.972	.331	(-.102;.303)

Note: If $p < .05$ for X then it is statistically significant and the moderator has a moderating effect for the direct path.

Table 41. Indices of moderated mediation revisit intention

X → Mediator → RI Predictor	Index	BootSE	95% Boot CI (LL;UL)
X → Trust → RI			
X1	.096	.086	(-.071;.264)
X2	.003	.094	(-.186;.180)
X → Intrusiveness → RI			
X1	.012	.051	(-.087;.116)
X2	.056	.056	(-.056;.166)
X → Vulnerability → RI			
X1	-.010	.027	(-.070;.041)
X2	.000	.028	(-.063;.051)
X → Privacy → RI			
X1	.011	.017	(-.019;.051)
X2	-.001	.019	(-.042;.037)

Note: If the confidence interval does not include zero for either the respective X1 or X2 variable, then one can state that there is proof of moderated mediation for that mediating variable. None of the variables in this table are statistically significant.

Table 42. PROCESS model 8 outcome variable word of mouth

WOM Predictor	Coeff	t	p	95% Boot CI (LL;UL)
constant	.831	2.662	.008	(.218;1.443)
X1	.075	.683	.495	(-.140;.290)
X2	.188	1.647	.100	(-.036;.411)
Trust	.536	14.512	.000	(.464;.609)
Intrusiveness	-.178	-4.607	.000	(-.253;-.102)
Vulnerability	.134	3.581	.000	(.061;.208)
Privacy	.221	5.520	.000	(.143;.300)
Moderato	-.154	-1.387	.166	(-.371;.064)
Int_1	.128	.820	.413	(-.179;.436)
Int_2	.046	.292	.770	(-.262;.354)
Age	-.048	-2.541	.011	(-.084;-.011)
Gender	.068	1.108	.268	(-.053;.189)
Education	-.055	-2.323	.021	(-.102;-.009)
Frequency	.128	4.882	.000	(.076;.179)
R^2	.601			

Note: If $p < .05$ for X1 or X2 then c'1 or c'2 path would be statistically significant. All the mediating variables are for the b-path. Mod is for the c'3 path, and Int_1 and Int_2 are for c'4 and c'5 paths respectively. For there to be a direct effect of the degree of AI surveillance on word of mouth, then either Int_1 or Int_2 has to be statistically significant. See figure 4.

Table 43. Relative conditional direct effects of X on word of mouth

WOM Predictor	Moderator	Effect	t	p	95% Boot CI (LL;UL)
X1	0	.075	.683	.495	(-.140;.290)
X1	1	.203	1.814	.070	(-.017;.423)
X2	0	.188	1.647	.100	(-.036;.411)
X2	1	.234	2.146	.032	(.020;.447)

Note: If $p < .05$ for X then it is statistically significant, and the moderator has a moderating effect for the direct path.

Table 44. Indices of moderated mediation word of mouth

X → Mediator → WOM			
Predictor	Index	BootSE	95% Boot CI (LL;UL)
X → Trust → WOM			
X1	.134	.117	(-.098;.371)
X2	.004	.131	(-.255;.255)
X → Intrusiveness → WOM			
X1	.012	.050	(-.086;.113)
X2	.053	.055	(-.047;.172)
X → Vulnerability → WOM			
X1	.015	.040	(-.063;.096)
X2	-.001	.040	(-.084;.078)
X → Privacy → WOM			
X1	.033	.044	(-.051;.124)
X2	-.002	.050	(-.103;.098)

Note: If the confidence interval does not include zero for either the respective X1 or X2 variable, then one can state that there is proof of moderated mediation for that mediating variable. None of the variables in this table are statistically significant.