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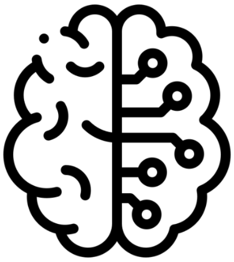

# Taking it personally?

A study on the effects of trust and privacy in the context of AI-enabled personalization

**Master Thesis**

MSc Marketing, Radboud University

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# 1. Introduction

We are living in an ever-changing world with a central role in data. With the rapid advancements of technology since the 1990s, digitization has rocketed the digital marketing field. Digital marketing can embrace the endless possibilities of data as the costs of collecting, storing, and interpreting consumer data have decreased tremendously (Bleier et al., 2020; Libai et al., 2020).

The rise of Artificial Intelligence (AI) is pivotal in these developments. A widespread definition of this phenomenon is the "system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaption" (Grewal et al., 2021, p. 230; Libai et al., 2020, p. 44). Based on the consumer data, AI is capable of understanding the customer and generating personalized responses accordingly (Aguirre et al., 2015; Bleier et al., 2020; De Bruyn et al., 2020; Grewal et al., 2021; Kumar et al., 2019; Libai et al., 2020; Thomaz et al., 2020). With a minimum effort, the customer now receives products, prices, and promotions at the right time, in the right spot, and the right manner. The personalization of this marketing mix thus enhances both the experience and the relationship with the organization (e.g. Aguirre et al., 2015; Bleier et al., 2020). Hence, Artificial Intelligence can be the answer to sustained margin pressures, shorter strategy cycles, and increased expectations from customers (Ameen et al., 2021). These answers can be devoted to dynamic pricing that can maximize profit margins, real-time market insights as a fundament for strategy formulations and personalized experiences to meet individual expectations.

Artificial Intelligence is therefore no exceptional term in marketing departments. Google combines the collected consumer data from their different platforms (i.e. Gmail and YouTube) to gain valuable insights into their customers. These insights form the marketing strategy in terms of customers to target and new products and/or services to develop. Yet, examples of the more day-to-day activities can for example be found in firms like Spotify, Netflix, and Amazon (Aguirre et al., 2015; Vlačić et al., 2021). They collect data on their consumers' behavior. The algorithms of Artificial Intelligence will then identify patterns and determine the predicting variables. Based on these insights, every customer will receive personalized recommendations (i.e. Discover Weekly on Spotify, recommended series on Netflix and products you might need on Amazon).

Nevertheless, Starbucks has taken all this one step further and has pioneered an app that enables a personalized experience for their customers with the help of Artificial Intelligence. This app has proven to be successful in, among others, the United States with rocketed sales as a result (Artificial Intelligence +, 2022). However, the Dutch population is generally acquainted with Starbucks a firm, yet the app is not available in this country. This opens up possibilities for the organization to roll out their success factor in the Netherland as well. However, as stated by Hong et al. (2021) culture can play a critical role in the success of Artificial Intelligence and personalization, as ‘personalization’ might be interpreted differently in different cultures. Therefore, it is relevant to explore the possibilities and opinions in the Netherlands before copy-pasting the concept one-on-one.

This research is, however, not only socially relevant. The contributions will be scientifically relevant as well. Artificial Intelligence has many potential and valuable benefits for the organization. Yet, integrating the algorithms in business activities is not without any risk. It is not without reason that literature asks for more insights into the concepts of trust and privacy in the context of Artificial Intelligence (e.g. Ameen et al., 2021; Bleier et al., 2020; Grewal et al., 2021; Hoyer et al., 2020; Thomaz et al., 2020; Vlačić et al., 2021). 91% of American customers feel like they have lost control over their personal information (Hong et al., 2021). Additionally, in this same survey, 70% of these customers have indicated that they are more concerned about their privacy now than they were years ago. This is reflected too in the fact that companies like Twitter, Facebook, and Google are all confronted with million-dollar lawsuits due to alleged breaches of privacy regulations (Hong et al., 2021).

Both trust and privacy are crucial for the success of AI applications in marketing. Artificial Intelligence lacks common sense. There is therefore no such thing as it goes without saying (De Bruyn et al., 2020; Luo et al., 2019). For example, Uber encountered this problem in 2017 after the terrorist attack in London (De Bruyn et al., 2020). The prices of a taxi are determined by an algorithm based on supply and demand. Due to the attack, everyone in the city tried to leave the city which caused a rush on taxis. As a result, Uber’s algorithm detected this peak in the demand and prices for a taxi drive went sky high. As a result, Uber still experiences reputational damage even though human employees were able to override the algorithm in minutes. A human understands that it is unethical to benefit from a terrorist attack and increase prices, Artificial Intelligence does not have this understanding. Uber hereby supports the fact that Artificial Intelligence can have a negative impact on the trust in the brand. Trusting the brand, then, is a ground reason for customers to be willing to invest in the brand and buy a product or service (Bart et al., 2005; Belanger et al., 2002; Wang & Benbasat, 2008). It is therefore important to gain insights into the antecedents of trust in the context of Artificial Intelligence, to maximize the gains by minimizing or eliminating the trust-related costs.

Along these same lines, there is a pressing need for insights into the antecedents of privacy concerns in the context of Artificial Intelligence as well. Consumer data is needed to find deep customer insights to act upon for the organization (Bleier et al., 2020). Ceteris paribus, the organization would thus strive to collect as much data as possible as this will increase the accuracy of the algorithm (De Bruyn et al., 2020). However, the more data is collected from a customer, the more concerns they will have about their privacy due to their vulnerable position (Aguirre et al., 2015; Belanger et al., 2002; Bleier et al., 2020; Hong et al., 2021; Vlačić et al., 2021). Privacy concerns affect the organization by dropping sales or ineffective online advertisements for example (Bleier et al., 2020). Therefore, the organization must have insights into how to prevent privacy concerns while still gaining optimal benefits from the potentials of Artificial Intelligence.

This research will thus complement the existing literature on trust and privacy by applying the theories in the context of Artificial Intelligence, specifically in the context of Starbucks' AI-enabled app. This will contribute to a deeper understanding of the antecedents so that organizations can act upon the insights to enhance trust and eliminate privacy concerns. Besides, this research will be socially relevant as it is addressing the possibilities for Starbucks' app to be implemented in a new context; the Netherlands. Therefore, this research will revolve around the following research question:

*"What are the roles of trust of privacy concerns in the context of AI-enabled personalization?"*

To investigate this research question, a survey will be conducted among the Dutch population. These results will be analyzed according to the PLS-SEM method. To structure the research, the next chapter will first cover the theoretical framework. The current state of the literature on Artificial Intelligence, personalization, trust, and privacy will be discussed. Thereafter, the Starbucks case will be further elaborated upon and the conceptual model will be discussed. After, in chapter 3, the methodology of this research will be discussed. This includes the data collection, method of analysis, and research ethics. The results of this analysis will then be brought to the attention in chapter 4. Both the measurement model and structural model will be analyzed and discussed sequentially. The last chapter will discuss the conclusions and limitations of this research as well as the managerial implications.

# 2. Theoretical Framework

## 2.1 Artificial Intelligence

Artificial Intelligence (AI). The mechanism with unprecedented power intrigues managers due to the expectation of endless possibilities. Nothing is less true, however. Artificial Intelligence is often misunderstood by managers on the ground of two conceptions (De Bruyn et al., 2020). First, managers proclaim AI to have endless possibilities. Yet the mechanism has its dangers and pitfalls too that ought not to be forgotten about. Moreover, the beneficial implications are often misjudged, resulting in misallocations of efforts and resources.

Artificial Intelligence is, on the other hand, "the system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Grewal et al., 2021, p. 230; Libai et al., 2020, p. 44). These abilities transcend human capabilities and the more traditional statistics like for example linear regression. The algorithms that drive Artificial Intelligence can contribute to knowledge creation by discovering hidden patterns and identifying higher-order constructs in data (De Bruyn et al., 2020). Nevertheless, Artificial Intelligence is an extensive concept that entails several varieties with differing implications. Figure 1 visualizes this matter and this will be further discussed in the following of this paragraph.

To start with, the concept of Artificial Intelligence can be broken down into Strong or General AI (AGI) and Weak or Narrow AI (ANI) as elaborated upon by multiple authors like De Bruyn et al., (2020), Grewal et al. (2021), Libai et al. (2020) and Wirth (2018). The most human-like of the two would be AGI (Libai et al., 2020), as these algorithms are able to learn how to learn. Hence, the algorithm of ANI is able to learn one specific task. For example, it can learn about a customer's music taste to recommend new songs on Spotify that fit this music taste.

Besides differences between algorithms in their strength, different algorithms can also learn different things. In non-business settings, symbolic AI can for example be very useful to learn and identify a blue circle or a red square. In business settings, however, the potential of deep learning and machine learning might be more relevant (De Bruyn et al., 2020). These algorithms learn to predict or identify patterns for example. In turn, this enables marketing to forecast actions and the behavioral implications such as the aforementioned Spotify example.

To be able to function properly, Artificial Intelligence will need learning paradigms or, in other words, training sets of data (De Bruyn et al., 2020). The learned rules and insights can then be extrapolated to the specific case at hand. Initially, this can be done via two ways of learning; supervised and unsupervised (De Bruyn et al., 2020). Unsupervised learning is done with a training set containing unstructured data. Therefore, there are no predefinitions or labels present in this data. The algorithm learning from plain text is an example of unsupervised learning. It will then defines relationships between words based on co-occurrences in this text. This requires the algorithm to be of such strength that unsupervised learning is often linked to AGI and deep learning (De Bruyn et al., 2020; Grewal et al., 2021). Despite its potential, it is rarely been put into practice due to its complexity.

On the contrary, supervised learning is linked to ANI and machine learning. Therefore, it is much more feasible to use and thus used more frequently (De Bruyn et al., 2020; Grewal et al., 2021). Supervised learning does require structured data and thus must the training set contain predefined labels (De Bruyn et al., 2020). Based on this data, the algorithm can then learn to find patterns and make predictions as mentioned above. Nevertheless, it can be quite an effort to prepare and structure the data as labels must often be assigned manually (De Bruyn et al., 2020). This opens up possibilities for a sustainable, competitive advantage (Libai et al., 2020). Having access to a well-prepared dataset enriches the resources of the company both in terms of the training set itself as well as the skilled employees to do so.

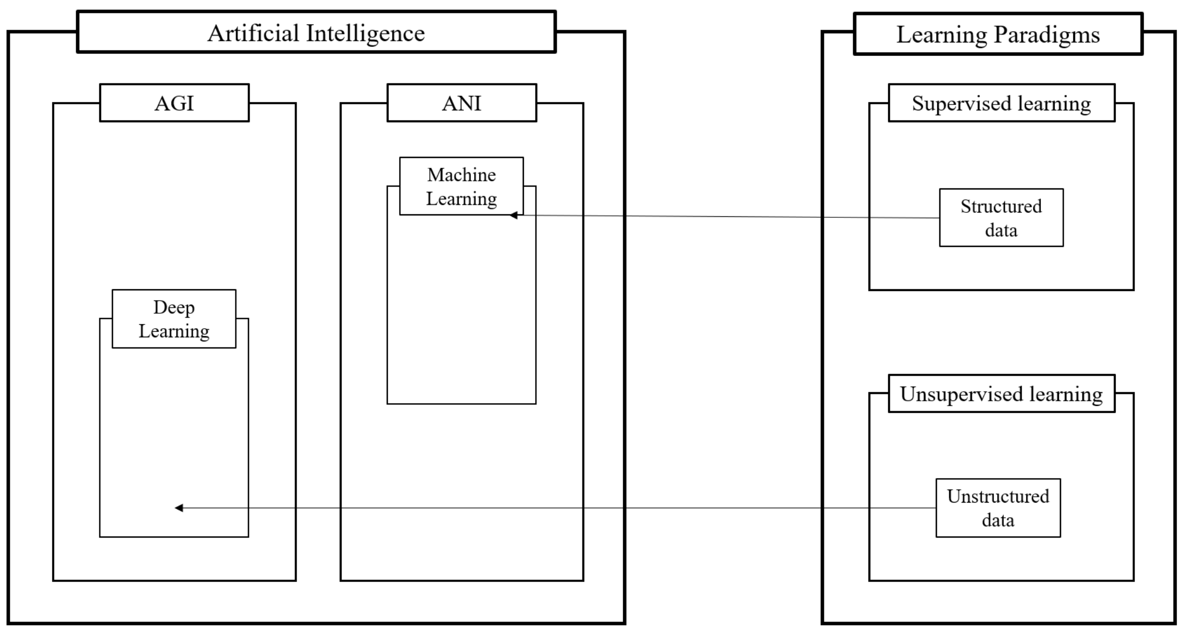


*Figure 1 Visualization of Artificial Intelligence*

Although Artificial Intelligence has many beneficial and powerful implications that are worth diving into, the ability to find patterns in data and extrapolate these insights to make predictions will be the most valuable asset of Artificial Intelligence for organizations. Therefore, this research will focus on Artificial Intelligence in the context of ANI and machine learning.

In this context, multiple data points are travelling through different layers of neural networks (De Bruyn et al., 2020). These algorithms will then reorganize and reconstruct this data into higher-order constructs. Ergo, these higher-order constructs function as the input for a selection of predictive variables that can be inferred to the cases at hand. In a business setting, the churn rates of customers can be forecasted based on recency and frequency measures for example.

Artificial Intelligence can thus be extremely beneficial for businesses. Nonetheless, integrating AI into business routines will not be without risks and threats. Both the opportunities as well as the risks will be discussed hereafter.

### *2.1.1 The advantages of Artificial Intelligence*

Artificial Intelligence can be advantageous for many business implications, one of them being marketing. Artificial Intelligence will have an elevating effect on the effectiveness and efficiency of marketing activities (Grewal et al., 2021). This will then pertain to the optimization of the marketing strategy, with a strong competitive advantage for the firm (Vlačić et al., 2021) as a result. Artificial Intelligence can improve the insights into consumers and their behavior (Ameen et al., 2021; Kumar et al., 2019; Libai et al., 2020; Thomaz et al., 2020; Tyrväinen et al., 2020; Vlačić et al., 2021). Understanding the customers' shopping preferences and patterns will enable the organization to act upon these insights and improve the customer lifetime value by personalizing the experience for every customer (Ameen et al., 2021; Grewal et al., 2021; Libai et al., 2020). In a setting with many transactions and interactions, there are a lot of touchpoints for a firm to collect consumer data. This is, among others, the case in for example banking, travel, and retail sectors (Grewal et al., 2021). Besides, online behavior on websites or social media can also be a fruitful source of information. With this vast amount of data, Artificial Intelligence can learn about the customer to the extent that the right product can be offered at the right time, at the right stage of the customer journey (Ameen et al., 2021; Grewal et al., 2021; Tyrväinen et al., 2020). Additionally, all interactions with the customer can be streamlined and optimized for the individual (Ameen et al., 2021; Hoyer et al., 2020; Kumar et al., 2019). Social media, for example, is a relatively new touchpoint that can be added to the customer journey. By exploiting both new and traditional touchpoints in the right manner and in a way that they add on to each other, the customer will experience a more pleasant and streamlined way of communicating that is perfectly suited to their personal preferences. By engaging customers in the right way and personalizing their experiences, even the top 1% of the customers can be reached and locked.

Artificial Intelligence also implies that a marketing strategy will shift from focusing on customer segments to individual customers and competing for them (Libai et al., 2020). It is therefore not only beneficial in the way that it can learn about the individual customer, but it can also keep track of competitors and general trends in the market as well (Libai et al., 2020). Having access to up-to-date insights is important in a way that the market will keep on changing. COVID-19, for example, caused a sudden run and extreme run on hand sanitizers and personal protection materials (Vlačić et al., 2021). Having access to such insights and being able to predict what the market will do thereafter, preceding the actual events, will provide the organization with an excellent opportunity to act proactively and make optimum use of market potentials.

Likewise, the overall efficiency of the firm's processes can be enhanced by Artificial Intelligence (Grewal et al., 2021). Amazon, for example, has optimized its checkout process. With the help of Artificial Intelligence the checkout processes of Amazon GO are now fully automated (Grewal et al., 2021). There are no cashiers as customers can quite literally grab their products and walk out of the store, without passing a cash register. Amazon's service costs are thereby lowered as employees are replaced by technology. Additionally, this technology can be exploited in every Amazon GO store. The fixed costs are thus spread over multiple stores and locations, which is beneficial due to its economies of scale (Ameen et al., 2021; Kumar et al., 2019; Libai et al., 2020).

### *2.1.2 The risks of Artificial Intelligence*

Artificial Intelligence is thus capable of discovering hidden patterns in data and transforming them into higher-order constructs, without any human intervention (De Bruyn et al., 2020). Based on these patterns and constructs, insights can be generated and patterns can be identified. These enable the above-mentioned benefits. Yet, this autonomy of the algorithm also has its pitfalls. Most of them relate to the fact that Artificial Intelligence can (re)produce biases due to either the data in the training set and/or the notion of endogeneity (De Bruyn et al., 2020; Libai et al., 2020).

Artificial Intelligence learns from a dataset that includes either structured or unstructured data. This dataset might (in)directly include social biases, for which Artificial Intelligence will possibly contribute to or shed light on social inequalities (De Bruyn et al., 2020; Libai et al., 2020). Due to Artificial Intelligence, businesses can, for example, conduct a marketing strategy of dynamic pricing. Product prices will then be adjusted to the customer's willingness to pay in such a way that they pay optimum prices. De Bruyn et al. (2020) elaborate upon an example in which dynamic prices raise ethical concerns. As they explain, women are often regarded as more vulnerable and amendable than men. In the case that this bias is present in the data training set, the algorithm will learn to use gender as a proxy for willingness to pay. Correspondingly, the algorithm will present women with higher prices for the same product as men will be presented. Even if the data set does not directly reflect this bias, it can contain information that will function as a proxy and still produce biases. Netflix has faced this problem for example (Bleier et al., 2020). Based on the data they have collected from this customer, they try to predict what films and series will interest the customer and recommend them. It seemed like the streaming platform was biased in its recommendations towards different ethnicities, despite this bias not being directly present in the dataset. Nevertheless, information on for example location, schools, professions, and income all functioned as a proxy for the notion of ethnicity. Hence, the algorithm found a pattern in the data that, by accident, reflected a social bias.

The second cause of biases is the concept of endogeneity (De Bruyn et al., 2020). In this case, the algorithm finds a relationship between a variable that is in the algorithmic model and a variable that is not included in this model. Therefore, the outcome of the model will be incorrect. This is an ordinary risk in Artificial Intelligence as the algorithm is trying to find hidden relationships. Also, Artificial Intelligence is often too complex for humans to fully understand how the algorithm works. Endogeneity in the dataset will thus be hard to identify. This can be problematic, as endogeneity works like a feedback loop and keeps on improving the accuracy of the model. In the example of predicting the churn rate of customers, for example, endogeneity can work as a self-fulfilling prophecy. Based on the input data, the algorithm will make predictions. One of these predictions could be that the customer is likely to churn. Accordingly, the firm might decide to invest less time and effort in this customer as they will not be profitable to this firm. As a result of this decision, the customer will most likely churn. Not because the data predicted this right, but solely as a result of the organization investing less time and effort in this customer. Considering the algorithm has made the right prediction, although, for the wrong reasons, the model will improve in accuracy.

These risks of Artificial Intelligence will be amplified when tacit knowledge is involved as well (De Bruyn et al., 2020). Artificial Intelligence, in the context of this research, differs from humans in way that it lacks common sense and the ability to learn how to learn (De Bruyn et al., 2020; Luo et al., 2019). In Artificial Intelligence there is no such thing that goes without saying. As humans, we understand that a marketing campaign ought to not break the law or endanger human life. Artificial Intelligence, on other hand, does not capture this notion and simply finds the best possible solution for the matter at hand.

The algorithms regarding Artificial Intelligence thus need objectified functions that are clearly defined (De Bruyn et al., 2020). That is problematic in a marketing context because this field specifically deals with tacit knowledge as it revolves around customer behavior and human interactions for example. It is hard to explicate this knowledge in such a way that the algorithm understands what is expected from them. Proposing the algorithm with the task to optimize the prices and promotions of products, seems like a clear task for humans. Nonetheless, Artificial Intelligence aims at finding the most simplistic solution and will quite likely come up with the idea to increase sales. However, this leaves out the fact that humans are not robots and that sales persons are incapable of eternally driving sales.

Not only is it difficult for humans to deliver the proper input for the algorithm, but this also works vice versa as well (De Bruyn et al., 2020). Artificial Intelligence can work autonomously and exceeds human capabilities in terms of analyzing data as mentioned before. As a result, humans are often unable to fully understand the way these algorithms work. On the one hand, one could argue that this is not a problem. There is no need for humans to understand all causal relationships, as long as the outputs of Algorithm Intelligence are clear and something they can work with. On the other hand, the trouble regarding the knowledge transfer from the algorithm to humans can be problematic. There is a certain need for humans to understand the data collection, as the algorithm can (re)produce biases. Causal relationships and malfunctioning training sets must then be manipulated by humans to overcome these biases.

### 2.2 Personalization

According to Grewal et al. (2021), Artificial Intelligence improves marketing effectiveness and efficiency through data-led personalization. The collected data can be analyzed faster and on a larger scale through Artificial Intelligence, than humans will be capable of (Ameen et al., 2021; Libai et al., 2020). As a result, marketing activities can be personalized for customers in terms of the user interface, content, and/or interaction processes (Belanger et al., 2002; Hoyer et al., 2020; Zanker et al., 2019).

Personalization has different definitions in the literature. Often, these definitions are similar to the one that Aguirre et al. (2015) have incorporated in their work. They define personalization as “a customer-oriented marketing strategy that aims to deliver the right content to the right person at the right time, to maximize immediate and future business opportunities”. Although not wrong, Kumar et al. (2019) take a more holistic view and incorporate the complete marketing mix in their definition. As stated by them, personalization “occurs when the firm decides, usually based on previously collected data, what marketing mix is suitable for the individual” (p. 136). According to Dibb et al. (2016), the marketing mix is the fundament of each marketing strategy and entails the product itself and its price, promotion, and place (distribution). Therefore, not only the content and timing of delivering this content can be personalized but also the way of interacting with the customer for example. For that reason, the latter definition by Kumar et al. (2019) better fits this research as it takes all opportunities for data-led personalization into account.

Personalizing the marketing mix for each customer has multiple benefits for the organization. To start with, the organization is able to extract all customer surplus (Aguirre et al., 2015; Grewal et al., 2021; Libai et al., 2020). As individual demand curves can be identified, the proposed prices to customers can be adjusted according to their valuations. This will result in maximized sales and revenues. On the one hand, the attention of the organization can be focused on the most profitable customers to gain the maximum benefits from them. On the other hand, the organization will still be able to extract value from the less profitable customers (Grewal et al., 2021; Libai et al., 2020). To guarantee a profit margin on the sold products, the organization can opt to offer a product of a lesser quality to the customers that are not willing to pay as much as the most valuable customers. The costs of production for these products are generally lower, which will sustain a profit margin on these products even with lower selling prices.

Secondly, personalization has beneficial effects on customer development and retention due to the notion of habit formation (Kumar et al., 2019; Libai et al., 2020; Thomaz et al., 2020). Customer development refers to the increase of the consumer's profit (Libai et al., 2020). This can for example be done by increasing the margins, increasing the frequency of buying and nudging the customer to upsell and/or cross-sell. Libai et al. (2020) identify the interrelationship between the retention and development of customers as well-developed customers are likely to stay loyal to the company for a longer period. The latter refers to the notion of customer retention. Both the customer's development and retention are strengthened by the customer's habits. These habits will be formed when organizations tap into the consumer's needs and preferences (Kumar et al., 2019; Libai et al., 2020). An optimal and personalized marketing mix will increase the customer's purchase intention (Hoyer et al., 2020; Tyrväinen et al., 2020). This purchase will then lead to new data about this customer, this data can provide the organization with new insights on the customer's behavior, this updated customer profile can then be used to strengthen the habit by again recommending the right product in the right manner (Kumar et al., 2019; Libai et al., 2020). The habit then encompasses buying both buying the product and buying the product from this specific organization. The automaticity of the habit, will increase the convenience of the buying process for the customer and thereby increase the switching costs to switch to another supplier of this same product (Libai et al., 2020; Tyrväinen et al., 2020). Amazon proves that this habit can even be acted upon proactively as the organization sends their customers products before they have even ordered them (Kumar et al., 2019). Amazon does so based on the buying habits of the customer and tries to make this habit even more convenient by making sure the customer does not even have to think about buying the product. In case the product is not needed, it can be returned free of charge. Yet in case the product is needed, the customer experience will have elevated and the relationship will be reinforced.

Personalization thus not only benefits the organization but also favors the customer too by the means of reducing search costs. The Internet provides the perfect ability to find every piece of information about anything in the world. Yet, this might result in an information overload for customers as they are cognitively restricted to a certain amount of processing power (Aguirre et al., 2015; Hoyer et al., 2020; Kumar et al., 2019; Tyrväinen et al., 2020; Wang & Benbasat, 2008). At a certain point in time, the customer will therefore not be able to process any more information that is needed to make a deliberate choice. Personalizing the pre-transaction phase means that only relevant information will be selected, the consideration set will be narrowed down to fewer products and the customer can even be advised on the best possible choice. This will reduce the customer's cognitive load significantly, resulting in an improved decision on the product or service. The perfect example for this matter would be the conversational agent 'Hello Hipmunk'. This agent, similar to Apple's Siri for example, aids customers in the journey of booking a holiday trip (Thomaz et al., 2020). Normally, booking and planning a trip would entail approximately 20 online searches. Hello Hipmunk reduces these 20 searches to only one conversation and helps decide on the perfect holiday trip. The conversational agent thereby aids in reducing the information overload to prevent a cognitive overload. A similar effect can be reached with for example recommendation agents and personalized landing pages on websites (Hoyer et al., 2020; Tyrväinen et al., 2020).

### 2.3 Trust & Privacy

In a world where data is playing an ever-increasing role, the factors of trust and privacy play a crucial part (e.g. Ameen et al., 2021; Bleier et al., 2020; Grewal et al., 2021; Hoyer et al., 2020; Thomaz et al., 2020; Vlačić et al., 2021). Even so in a business context, where customer relationships have to be maintained despite they are making a shift from an offline to an online focus (Bart et al., 2005). Nowadays, customers are relying more and more on the Internet as their source of information and purchases.

To start with, trust can generally be described as "a psychological state comprising the intention to accept vulnerability based on positive expectations of the intentions or behaviors of another" (Bart et al., 2005, p. 134). Ameen et al. (2021) complement this definition by explicating trust in the context of online commerce. In the online context, trust does not only entail trusting the brand but the technology too.

At the basis of trust lies the perception of trustworthiness (Bart et al., 2005; Belanger et al., 2002; Wang & Benbasat, 2008). As a customer, you expect the organization to be benevolent, integer, and capable to perceive them as trustworthy. Trust in a long-lasting buyer-seller relationship is important as this relationship is asymmetric. Often, the organization has a more powerful position than the customer when it comes to knowledge about the other party (Aguirre et al., 2015; Grewal et al., 2021). The organization is for example able to continuously update its knowledge and insights about its customers and their behavior by exploiting the power of Artificial Intelligence. Something the customer will have a lot more problems with. As a result, the customer will face a fear of exploitation (Aguirre et al., 2015; Grewal et al., 2021; Thomaz et al., 2020). They are in a vulnerable position in

which the organization can mistreat the customer. In this case, the customer's perception of the benevolence, integrity, and ability of the organization is breached. This breach will affect their interaction with the organization and negatively impact their intention to buy a product or service (Bart et al., 2005; Belanger et al., 2002; Wang & Benbasat, 2008).
Of course, this works vice versa as well. In case the organization treats the customer fairly and equally, the consumer's trust in the brand will grow. This will have a positive effect on the consumer's behavioral intent and the prices they are willing to pay (Bart et al., 2005; Belanger et al., 2002; Wang & Benbasat, 2008).

An important addition to the notion of trust in an online setting is the fact that consumers generally prefer human interactions over interactions with a machine or technology (Aguirre et al., 2015; Ameen et al., 2021; Hoyer et al., 2020; Thomaz et al., 2020). This notion is grounded in the fear of uniqueness neglect by an AI-enabled application for example. In other words, customers trust the recommendations that are done by a human more than the recommendations that are provided by an online recommendation agent, especially when it comes to their personal preferences. In their opinion, a human is more capable of advising which painting to buy or what tattoo to choose because a human is more capable of capturing and understanding their personal preferences. An online recommendation agent is in advance already less trusted in this decision as it lacks emotional intelligence (Ameen et al., 2021; Bleier et al., 2020; Wang & Benbasat, 2008).

Aside from trust is privacy a pressing concern as well in the rise of digital marketing. Privacy will be best described as "the protection of individually identifiable information on the Internet, and it involves the adoption and implementation of a privacy policy, notice, disclosure, and choice/consent of the Web site visitors" (Bart et al., 2005, p. 135). Privacy will affect the organization in multiple ways. Apart from litigation risks, violation of privacy measures will likely cause data foreclosure and dropping revenues too as consumers will be precautious and/or demotivated to share any personal information as well as buy any products or services from the firm (Bleier et al., 2020). These dropping sales will of course directly press the revenues, but a privacy breach will indirectly affect revenues as well. Consumers will be less likely to click on digital advertisements, install ad blockers and/or opt-out of leaving an online footprint. Additionally, adhering to obliged privacy regulations will narrow down the scope of the marketing strategy as well (Bleier et al., 2020). Especially innovations will be cut back as consumer's data cannot be used for other purposes than for what it was initially collected. Generated insights could therefore have been valuable input for innovations, yet are useless due to privacy regulations.

Relevant in this context is the notion of a privacy calculus (Bleier et al., 2020; Hong et al., 2021). Whilst online interacting with a firm, customers have to decide on whether or not to disclose personal information. Sharing personal information puts them in an uncertain and vulnerable position (e.g. Aguirre et al., 2015; Belanger et al., 2002; Bleier et al., 2020; Hong et al., 2021; Vlačić et al., 2021). Sometimes the uncertainty is related to the fact that the source of the data is relatively new and this data can be used for different purposes as well. Such a source might for example be the Fitbit. This is a watch that tracks one's daily activities and health indicators. This data can be quite relevant for insurance companies for example, as it will provide them insights into the risks of their customers getting ill or injured. Therefore, sharing the collected by a Fitbit can put customers in a vulnerable and uncertain situation as the outcomes will not always be beneficial to them (Bleier et al., 2020). The degrees of vulnerability and uncertainty are then weighed against the value they will get in return. Along those lines, firms can overcome this privacy calculus by either lowering the concerns regarding privacy or increasing the value customers will get in return for sharing their data (Hong et al., 2021).

### 2.4 Putting it all together: The Conceptual Model

As elaborated upon above, Artificial Intelligence has both a lot of potential and a lot of pitfalls with two pressing concerns; trust and privacy. Therefore, this research will be conducted in the light of a real-life case; Starbucks' Deep Brew platform. It will narrow down the field of Artificial Intelligence to those implications that are relevant to Starbucks, such that the research is feasible to do with the provided time frame and resources. Hence, the following paragraph will elaborate upon the Starbucks Deep Brew platform. Thereafter, the conceptual model of this research will be constructed and explicated.

#### *2.4.1 Starbucks Case: The Deep Brew Platform*

It is the year 1971. In the streets of Seattle, the first doors are opened of what is known today as Starbucks. Over the years, they have spread across the world and welcome millions of customers per week in their coffee stores. It is, therefore, safe to say that Starbucks has developed itself to become the world's most well-known coffeehouse. Day in and day out, its employees contribute to Starbucks' mission: "To inspire and nurture the human spirit – one person, one cup, and one neighborhood at the time" (Starbucks Coffee Company, n.d.). Personalization is thereby part of Starbucks' DNA. It is tied to their mission to encounter every customer and every cup of coffee individually. In other words, every customer is immersed in an unique customer experience. This customer experience, according to Starbucks (Starbucks Coffee Company [Microsoft Developer], 2019) is elevated by convenience and consistency. Hence, the company has developed a mobile app to tap into this elevation of the customer experience.

This app, which is described by Starbucks as their 'Deep Brew platform', started as a loyalty program for customers in 2019 (Peiper, 2020; Artificial Intelligence +, 2022; Hyperight, 2021). By sharing their location, customers can select the products, customize them according to their personal preferences and order their food or beverage. The app will then identify the most convenient store location and estimate the waiting time before the order can be picked up (Peiper, 2020). Stars can be earned with every order that is done in this in this app. These stars can then later be exchanged for interesting deals at Starbucks. Over time, the app also started to function as an information center on for example opening hours and store locations.

The COVID-19 pandemic has rocketed the app's potential (Peiper, 2020; Artificial Intelligence +, 2022; Hyperight, 2021; World Business Research, 2020). The virus has asked for measures to social distance and minimize physical contact. Therefore, alternatives had to be found for day-to-day activities. This Starbucks app has enabled the store to offer services like digital payments and contactless pick-ups and deliveries.

Offering these services in itself can pertain to the customer experience if the services are of high enough quality. Nonetheless, as mentioned before, Starbucks elevated its customer experience by introducing the mobile app. Customers provide a substantial amount of data when using the app. Some are related to the transaction itself, such as data on the ingredients and bought products. Other sources of data are related to the location of the customer, like the weather and time of the day. In other words, both semi-structured and unstructured data are collected by Starbucks via the Deep Brew platform (Starbucks Coffee Company [Microsoft Developer], 2019; Artificial Intelligence +, 2022). This vast amount of data has resulted in several challenges for the coffee house. The platform should stay both functional and user-friendly (Starbucks Coffee Company [Microsoft Developer], 2019; Artificial Intelligence +, 2022; Hyperight, 2021). This implies that for customers it should still be useful and easy to use. On the other hand, Starbucks must still be able to gain valuable insights and therefore be able to isolate specific services and regions for example.

Starbucks has been able to overcome these challenges. Nowadays, about 25% of Starbucks' orders are placed via this app (Artificial Intelligence +, 2022; Hyperight, 2021). These orders generate plenty of data, which is then processed by AI algorithms. With the help of machine learning, these insights are translated into actions that personalize the customer experience for every individual customer (Starbucks Coffee Company [Microsoft Developer], 2019; World Business Research, 2020). In other words, AI drives personalization activities (Artificial Intelligence +, 2022; Hyperight, 2021; World Business Research, 2020).

With this level of personalization, Starbucks aims to maximize profits by fulfilling two major goals; upselling and cross-selling products (Starbucks Coffee Company [Microsoft Developer], 2019). Having such a deep and detailed understanding of every customer, Starbucks can proactively recommend products to her customers that fit their exact needs and preferences (Starbucks Coffee Company [Microsoft Developer], 2019; Artificial Intelligence +, 2022; Hyperight, 2021). A meat sandwich will never be recommended to a vegetarian, and a basic black coffee will never be recommended to the customer who always goes for the fancy coffees.

These recommendations pop up in the app, or via push notifications on the customer's mobile phone. These are based on both the customer's prior purchases, as well as on context variables like the time of the day, the customer's location, and the weather of the day. Because these recommendations are done proactively, the customer might not even have thought of buying for example a coffee themselves. Yet, they are buying a coffee now because Starbucks is now on top of their mind. In addition, Starbucks can recommend a bigger coffee or a sandwich to go with this coffee for example, which might uplift the actual spending of the customer. Hence, Starbucks' mobile app elevates the customer experience by personalizing it exactly to the individual's preferences (Starbucks Coffee Company [Microsoft Developer], 2019).

Additionally, the mobile app enables Starbucks to optimize its way of doing business as the gathered data provides insights into the purchase behavior of customers. These insights can be used as input for the development of new products (Artificial Intelligence +, 2022; Hyperight, 2021; World Business Research, 2020). For instance, the 'Mango Green Iced Tea' and 'Peachy Black Tea' are both iced tea without added sugars. These products have entered the Starbucks menus as a result of the fact that Starbucks learned that 43% of the tea drinkers do not add any sugar to their tea (Artificial Intelligence +, 2022; Hyperight, 2021).

Secondly, Starbucks is now able to thrive under a zero-waste strategy for two reasons (Starbucks Coffee Company [Microsoft Developer], 2019; Artificial Intelligence +, 2022; Hyperight, 2021; World Business Research, 2020). To start with, needed inventory can be predicted based on the data of customer purchase behaviors. Secondly, these same purchases can be adjusted to the inventory at hand. For example, in the case of a surplus of a certain ingredient, certain food or beverage can be promoted to improve sales and use up the ingredient surplus. In the end, this will reduce waste as the inventory and sales are almost perfectly matched.

Furthermore, the opening of new store locations can be further optimized by the insights into consumer data (Starbucks Coffee Company [Microsoft Developer], 2019). By offsetting the local income levels and the presence of competitors, Starbucks can identify the most profitable locations to open up new stores. This means that not only general and public information is used, but also more private and sensitive information is used by Starbucks to improve their business activities.

One can thus state that Starbucks has integrated the use of AI into its daily business routines. Although they are very successful in doing so, they must be aware of the privacy and trust issues that their customers might have due to the use of their personal data (Starbucks Coffee Company [Microsoft Developer], 2019). Starbucks identifies itself as a trusted brand (Starbucks Coffee Company [Microsoft Developer], 2019). Therefore, the trusted relationship with their customers is of great importance to them, whilst on the other hand, they are trying to provide the most advantageous convenience to their customers. For the latter, they will need the AI algorithms as elaborated on above. Practice implies that the coffee house perfectly balances the thin line of providing convenience whilst maintaining trusted relationships (Artificial Intelligence +, 2022). By providing recommendations proactively, Starbucks proves to master customer loyalty as their customers feel seen and understood.

Along these lines, Starbucks attempts to minimize trust and privacy concerns by opening up about how they collect and use their customers' data (Starbucks Coffee Company [Microsoft Developer], 2019; Artificial Intelligence +, 2022; Hyperight, 2021; World Business Research, 2020 ). They open up about how they have built the database and software themselves and gather their own data. Hence, the gathered data is only in hands of Starbucks and will not be used for other purposes nor will it be in the hands of other companies.

*2.4.2 Hypotheses development*

So far, this chapter has elaborated upon the status quo in literature regarding the constructs of Artificial Intelligene, personalization, trust, and privacy. Thereafter, the Starbucks case of the Deep Brew platform has been substantiated upon. In the latter of this chapter, the hypotheses will be developed by combining the litature insights with the Starbucks applications.

To start with, Starbucks' marketing strategy is to elevate the customer's intent to upsell and/or cross-sell. Every marketing-related activity will have to have a positive effect on these constructs to be in line with the company's objectives. Thus, as visualized in figure 2 'customer's intention to upsell' and 'customer's intention to cross-sell' are included in the conceptual model as the dependent variables. Hence, this research will aim to explain the variance in these constructs and provide insights into how to optimize these. As mentioned before, this will be addressed by the following research question: *"What are the roles of trust of privacy concerns in the context of AI-enabled personalization?"*

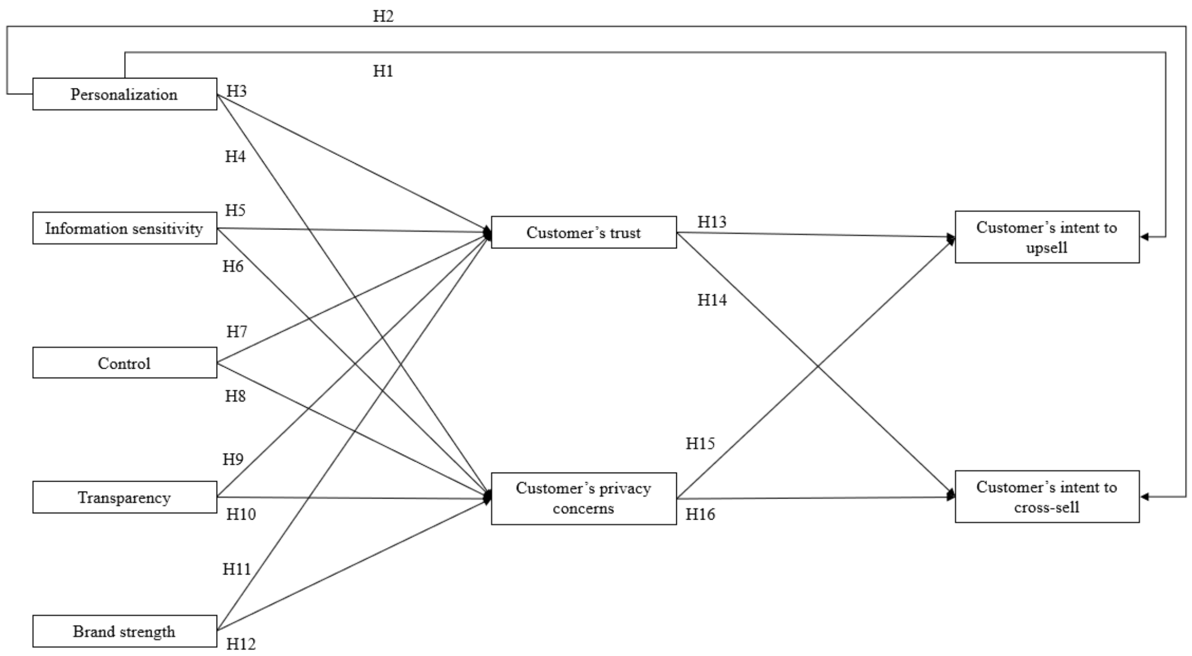


*Figure 2 Conceptual Model*

Following both Starbucks' vision and the literature, AI-enabled personalization will directly contribute to increasing the customer's intention to upsell (i.e. a larger coffee) and/or cross-sell (i.e. an cookie on the side with that coffee). Proactively recommending a coffee that is adjusted to the customer's preferences, is a way of optimizing the marketing mix for the individual customer as the right product is offered at the right time, with the right communication. As elaborated upon earlier, personalizing the marketing mix will result in increased purchase intentions (e.g. Hoyer et al., 2020; Tyrväinen et al., 2020). These purchase intentions in this case are the customer's intent to upsell and/or cross-sell. Therefore, the first hypotheses are:

*H1: Personalization has a direct positive effect on the customer's intent to upsell.*

*H2: Personalization has a direct positive effect on the customer's intent to cross-sell.*

Nevertheless, both Starbucks and the literature identify the challenge related to trust and privacy when implementing Artificial Intelligence in the operational processes. To start with, concerns about biases can be a prominent problem for customers to trust Starbucks. As mentioned above, Artificial Intelligence can (re)produce social biases from the learning paradigm as it discovers hidden patterns and forms higher-order constructs. This is either because the bias itself or the proxies to social biases are present in the training set (e.g. De Bruyn et al., 2020; Libai et al., 2020). If the algorithm finds or produces these biases, they will reflect in the recommendations that are done to the customer. Hence, the feeling of being presented with biased recommendations (e.g. only too expensive coffees) breaks down the trusted relationship between the brand and the customer for the brand breaching the preconditions of benevolence, integrity, and ability (e.g. Grewal et al., 2021; Wang & Benbasat, 2008). Besides, consumers tend to trust a human decision more than they trust the recommendation of an online agent with the help of Artificial Intelligence, due to the lack of emotional intelligence of the latter (Ameen et al., 2021; Bleier et al., 2020; Wang & Benbasat, 2008). Therefore, the next hypothesis will therefore be:

*H3: Personalization has a negative direct effect on the customer's trust.*

Accordingly, Starbucks uses quite some personal information (i.e. location, prior purchased products, willingness to pay) of their customers to come up with personalized recommendations. This amount of data will weigh heavily on the privacy calculus' scale. The benefits of sharing this data must outweigh the risks of sharing the data and the customer putting himself or herself in a more vulnerable position. Thus, the more data is needed to personalize the recommended coffee, for example, the more likely that the customer will develop concerns about their privacy. The fourth hypothesis will thus be formulated as followed:

*H4: Personalization has a positive direct effect on the customer's privacy concerns.*

In addition, the presented Starbucks case identifies other constructs that will influence the customer's trust and privacy concerns as well. That is to say the information sensitivity, control, transparency, and brand strength.

*Information sensitivity:* Information can vary in its level of sensitivity (Bleier et al., 2020; Hong et al., 2021). Financial information and information that is personally identifiable (i.e. name, phone number, social security number) are generally considered to be sensitive. In contrast, data on for example media consumption, demographics, and lifestyle interests are generally considered to be less sensitive. For the execution of the Deep Brew platform, Starbucks uses both sensitive and less sensitive information. Hence, the more sensitive the shared information, the higher the related risks (Bart et al., 2005; Bleier et al., 2020; Grewal et al., 2021). To start with, these risks will have an impact on the buyer-seller relationship as it will emphasize the asymmetry. Secondly, these risks will again weigh heavily on the privacy calculus and thus likely stimulate privacy concerns. Therefore, hypotheses five and six are formulated:

*H5: Information sensitivity has a negative direct effect on the customer's trust.*

*H6: Information sensitivity has a positive direct effect on the customer's privacy concerns.*

*Control:* The consumer's control over their data can take multiple forms (Hoyer et al., 2020; Wang & Benbasat, 2008). For example, the consumer can be provided with choices over what product to buy, or what specific data will and will not be shared with the company. Consumer's control can also be the opportunity to express the needs and preferences that should be taken into account by the organization. In the provided Starbucks case, the consumer is for example in control over what product(s) to buy as they can further customize this according to their wishes. The consumer's control will enhance their trust in the brand as the relationship is more symmetrical and the customer is less likely to be misused by the organization (Aguirre et al., 2015; Wang & Benbasat, 2008). In addition, having control over the shared data will reduce privacy concerns as the risks can be minimized by the customer himself or herself. Therefore, the following two hypotheses are defined:

*H7: Control has a positive direct effect on the customer's trust.*

*H8: Control has a negative direct effect on the customer's privacy concerns.*

*Transparency:* Starbucks provides transparency to such a degree that they open up on how their algorithm works and what is done with the collected data. In the literature, transparency is often interrelated with control (Belanger et al., 2002; Bleier et al., 2020). The principle of ‘notice and consent’ concerning a privacy statement for example is an opportunity for the customer to grasp control. At the same time, they are being informed on what will be done with their data and for what reasons it is collected. Both Aguirre et al. (2015) and Bleier et al. (2020) explain the effects of transparency on privacy concerns by using the example of personalized advertisements. As they state, being confronted with a personalized advertisement without any insights into how this ad has been established, will likely result in suspicions about the data flows. It will tap into a feeling of inappropriateness due to the vagueness of where this data is coming from and what exactly has been done with it. In other words, the customer will develop concerns about their privacy. Along these same lines, without any insights into how this advertisement is established, this also means that a customer cannot judge this advertisement on its bias for example and thus negatively impacts the customer’s trust (e.g. Aguirre et al., 2015; Grewal et al., 2021; Thomaz et al., 2020; Wang & Benbasat, 2008). Therefore:

*H9: Transparency has a positive direct effect on the customer’s trust.*

*H10: Transparency has a negative direct effect on the customer’s privacy concerns.*

*Brand strength:* Starbucks describes itself as a trusted brand. This is beneficial in the case of the Deep Brew platform as customers have little to no understanding of how Artificial Intelligence works. In such a situation, a brand can function as a trust mark (Bart et al., 2005; Hoyer et al., 2020). A customer will associate the brand with certain standards concerning quality and security. CocaCola is a strong brand known all over the world and tastes the same no matter the country (Urban et al., 2000). Hence, the customer knows what to expect from the drink even in a country where they are not acquainted with the local drinks. The same type of thinking can be applied to the security standards of the brand. They, too, provide clearity in uncertain situations. Hence, the hypotheses are formulated:

*H11: Brand strength has a positive direct effect on the customer’s trust.*

*H12: Brand strength has a negative direct effect on the customer’s privacy concerns.*

At last, as mentioned prior in this chapter, trust and privacy both have their effects on business outcomes like sales, revenues, and purchase intentions (Bart et al., 2005; Belanger et al., 2002; Bleier et al., 2020; Wang & Benbasat, 2008). Nevertheless, literature disagrees on the relationship between the two. Some researchers have identified privacy as an antecedent to trust (Bart et al., 2005; Hong et al., 2021), others have defined this relationship the other way around and define trust as a driver of privacy (Bleier et al., 2020; Thomaz et al., 2020). However, this research aims to investigate the mediating roles of both trust and privacy in an Artificial Intelligence context. Therefore, both constructs will be treated separately to be able to conclude both constructs separately. As a result, the last hypotheses are defined as followed:

*H13: Customer's trust has a positive direct effect on customer's intent to upsell.*

*H14: Customer's trust has a positive direct effect on the customer's intent to cross-sell.*

*H15: Customer's privacy concerns have a direct negative effect on the customer's intent to upsell.*

*H16: Customer's privacy concerns have a direct negative effect on the customer's intent to cross-sell.*

# 3. Methodology

### 3.1 Data collection

For this study, data has been collected amongst the Dutch population via a survey that has been established in Qualtrics. The survey has therefore been translated to Dutch. Nevertheless, both the Dutch and English versions can be found in Appendix 1 of this research.

As indicated in Appendix 1, the survey indicators have been established by combining multiple articles in the field that have researched one, or more constructs before. In addition, the Starbucks case has been developed specifically for this research and therefore has not yet been used in prior research. Therefore, the survey had to be pretested before publication to reduce biases due to misinterpretation. This pretest has been done with 5 personal contacts of the researcher. These respondents are all objective as none of them were already familiar with the Starbucks case. Additionally, the respondents were heterogenous in terms of their differences in age and gender. This pretest pointed out that the case itself was unambiguous as all the filtering questions had been answered with ‘yes’. However, the items in the questionnaire itself had proven to be long with complex clauses in the sentences. Specifically, the Dutch clause “die wordt gedreven door kunstmatige intelligentie” turned out to hinder the readability of the questions. This clause is of methodological relevance as it clearly refers to the previously read case in the survey and therefore reduces biases. Nevertheless, the structure of the sentences has been critically reviewed and adjusted wherever possible to improve the readability of the questions. After doing so, the survey has been published.

As mentioned above, the questionnaire is spread across the Dutch population. The mobile app has not yet been launched in this country, which opens up possibilities for the implications of this research. Critical success factors can be identified and implemented when launching the app. Concerning the age of the population, no boundaries have been set for the mere reason that the products sold by Starbucks with regard are available for all ages. There are no such restrictions as with alcoholic drinks for example.

To make sure that respondents can answer all questions and reduce any biases due to a lack of understanding, they have been posed with filtering questions at the start of the questionnaire. As a result, every respondent who has finished the questionnaire has the same understanding of AI, personalization, and the case at hand.

By continuing the questionnaire, the respondents are faced with multiple statements to answer on a 5-point Likert scale. As stated by Brinkman (2014), Likert scales are prominently useful for measuring constructs like attitudes and characteristics and therefore very convenient for this study. Additionally, a 5-point Likert scale ranging from ‘strongly agree’ to ‘strongly disagree’ has been chosen because the answers will be easier to interpret.

Also, the questions are grouped per measured construct. This keeps the survey coherent for the respondents and thereby motivates them to finish the survey. Furthermore, the direction of the questions is consistent per construct, yet altered between the constructs. Consistency in the positive or negative tone of the questions will prevent confusion for both the respondents and the software that will later be used for the analysis. Nevertheless, altering the tone between the constructs prevents respondents from automatically answering the questions without really reading them (Brinkman, 2014). It keeps them alert and motivated to read the questions carefully. Hence, biases in the results will again be reduced.

Lastly, respondents are all forced to answer questions in two ways. To start with, the next page will only load if all prior questions have been answered. Therefore, the questionnaire cannot be finished without answering all questions. Secondly, there is no option provided like ‘I don’t know’ or ‘not relevant’. Consequently, respondents are forced to think about an answer. A middle category like ‘neither agreed nor disagreed’ has been added as there might still be statements about which the respondent will not have a clearcut opinion.

### 3.2 Method of analysis

To further investigate the presence and significance of the hypotheses that have been posed in chapter 2, a quantitative analysis of the survey results will be needed. This study is best suited for Structural Equation Modelling as this is a “family of statistical models that seek to explain the relationships among multiple variables” (Hair, Black, Babin & Anderson, 2019, p. 607). This family of statistical models has two major methods; Covariance Based Structural Equation Modelling (CB-SEM) and Variance Based Structural Equation Modelling; to which Partial Least Squares Structural Equation Modelling (PLS-SEM) belongs according to Hair et al. (2019).

As Hair et al. (2019) state, there are structural differences between CB-SEM and PLS-SEM that make them suitable for different kinds of research. To start with, PLS-SEM is primarily aimed at explaining the variance in the dependent variables in the best possible way. Oppositely, CB-SEM is mainly aimed at confirming theories. This makes PLS-SEM more suitable for exploratory research as well. Meaning that PLS-SEM is able to address less defined research problems and all types of research questions. Rather than addressing a very specific, pre-defined, theory confirming the research objective. Additionally, PLS-SEM is convenient for predictive modeling. This enables the researcher to draw conclusions based on for example statistical significances of relationships, the relative importance of antecedents, explained variances, and effect sizes. Furthermore, PLS-SEM can handle a bigger model complexity with rather small sample size. The number of constructs per model is approximately eight in a PLS-SEM study compared to five constructs in a CB-SEM study (Hair et al., 2019). Besides, PLS-SEM has a higher statistical power which means that it still can come up with meaningful solutions with even a relatively small sample size.

Hence, this study will obtain the principles of the PLS-SEM study as it aimed at investigating the relationships between multiple constructs to be able to maximize the explained variance in the dependent variables ‘customer intention to upsell’ and ‘customer intention to cross-sell’.

The model for an SEM analysis consists in first place of endogenous and exogenous variables (Hair et al., 2019). These are synonyms for respectively the independent and dependent variables in a model and are indicated by the elliptical shapes in figure 3. In other words, the endogenous variables are measured by the exogenous variables in a model. These exogenous variables are latent in nature, meaning that they cannot be measured directly. Instead, they are constructed by multiple indicators. These indicators, in their turn, are either reflective or formative in nature (Hair et al., 2019). In this study on trust and privacy in the context of AI-enabled personalization, the constructs are represented by their indicators rather than formed by their indicators. Thus, this study makes use of a reflective measurement model as indicated. The associated indicators per construct are presented in figure 3XX as rectangular shapes.

This measurement model is one of two models that PLS-SEM will assess, as depicted by Hair et al. (2019). Figure XX represents the path model in which models are visualized. Along the lines of PLS-SEM, and as elaborated upon by Hair et al. (2019), the validity of the measurement model will be assessed first. The measurement model is also known as the outer model in PLS-SEM and includes the indicators and their relationships with the constructs. These are thus visualized in figure 3 by the black arrows that point from the construct to the associated indicators. As mentioned before and indicated by the direction of the black arrows, these are reflective in nature. The assessment of the measurement model will therefore address four different aspects (Hair et al., 2019):

- *Indicator loadings*: the construct must explain a considerable amount of the variance in the specific indictor. The indicator loadings must at least be .70 (Hair et al., 2019).
- *Construct reliability*: this refers to the internal reliability of the construct. In other words, it investigates to what extent the indicators measure the construct. This is often indicated by Cronbach's alpha and should thus be above .70 (Hair et al., 2019).
- *Convergent validity*: this elaborates on the extent to which the indicators converge on the associated construct. Thus, this investigates the variance in the indicators that are explained by the construct. This aspect is often reflected in the AVE and should be above .50, meaning that the construct accounts for at least 50% of the variance in the indicators (Hair et al., 2019).
- *Discriminant validity*: the discriminant validity then investigates the distinction of one construct from the other constructs. It thus provides insights into the uniqueness of the indicators in relation to the construct. They should load best on the associated construct and not cross-load on the other constructs. This fourth aspect is often indicated by the HTMT and should be below .85 (Hair et al., 2019).

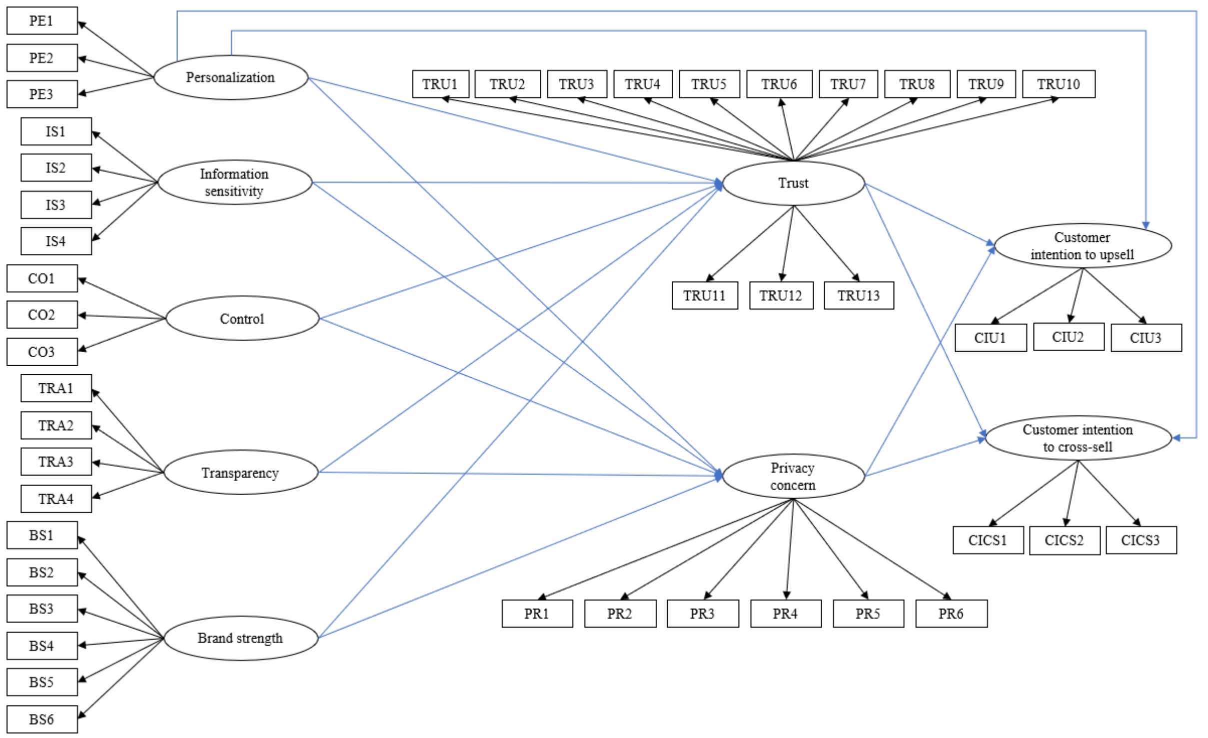


*Figure 3 PLS-SEM path model*

Only when the measurement model is determined satisfactory, the structural model will be assessed. The structural model is also referred to as the inner model (Hair et al., 2019) and is indicated with the blue arrows in figure 3. Therefore this model addresses the endogenous and exogenous variables and their relationships. Assessing the structural model implies diving into four aspects (Hair et al., 2019):

- *Collinearity among predictor variables:* collinearity among the predictor variables might confuse the interpretation of the results, as at least one predictor variable can be explained by the model. Identification of the collinearity can be done by interpreting the VIF values and looking into the bivariate correlations. A VIF value of more than 5 indicates a problem related to collinearity, as well as the values of the bivariate correlations exceeding 0.50.
- *Coefficient of determination*: the coefficient of determination addresses the predictive power of the model, and thus taps into the main objective of PLS-SEM. This predictive power is indicated by $R^2$. The higher this value, with a maximum of 1, the stronger the predictive power.
- *Effect size*: the effect sizes are related to the exogenous variables in the model. The effect size determines the change in the predictive power of the model when the exogenous variable is removed. The identification of this effect is based on $f^2$.
- *Substantiality of effects*: the substantiality of the effects focuses on the size and significance of the path coefficients. Determining the significance is by taking different samples from the sample and comparing the results. This method is also called bootstrapping, and thus corrects for biases.

These analyses have been executed in the SmartPLS3 software. Chapter 4 will elaborately discuss these results.

### 3.3 Research ethics

This research has taken multiple ethical considerations into account. To start with, 97 respondents have participated in the survey. To guarantee their privacy, their participation is fully anonymous. No personal identifialbe information has been collected. It is therefore impossible to expose this data in this research. As this data is solely collected for the purpose of this research, it will also be destroyed after processing. Lastly, participants have been explicitly informed about their right to terminate the survey at any point in time. Hence, they have not been obliged to provide any information they have not been willing to share.

In terms of intelluctual property, this research has been established in correspondance with the 7th edition of the APA guidelines. Multiple articles have been used to inform the researcher on the discussed topics. Nevertheless, these articles and authors are all being referred to when their work has been infused in this research. Thus, the authors are all credited for their own work and efforts.

# 4. Results

Before running the data in SmartPLS3 software, the data has been cleaned and prepared for analysis. The survey has been filled out by 97 respondents in total. 10 of these respondents have been deleted from the dataset because they did not meet the requirements regarding their understanding of the case, Artificial Intelligence, and/or personalization. Or, they do not live in the Netherlands. As indicated in the prior chapter, these filtering questions were needed to reduce biases in the dataset. Therefore, the analysis will be based on the results of 87 respondents, thereby meeting the requirements for the minimum sample size. The minimum sample size would be 10 times the number of the maximum number of latent variables per construct (Hair et al., 2019). In this research, the minimum sample size would therefore be 50 respondents.

Additionally, the data has been re-labeled before analyzing to make them easier to interpret and suitable for the SmartPLS software. All survey items have been answered on a 5-point Likert scale, ranging from strongly agree to strongly disagree. These items have been valued numerically accordingly; strongly agree (5), agree (4), neither agree nor disagree (3), disagree (2), and strongly disagree (1). Thus, the higher the value, the stronger the respondents agree with the proposed statement and vice versa.

After cleaning and preparing the data, this dataset has been loaded into the SmartPLS software. Based on this, the path model has been constructed and the PLS algorithm has been calculated. The result of this analysis will be discussed in the latter of this chapter.

### 4.1 Outer Model Analysis

As stated by Hair et al. (2019), the outer model, also referred to as the measurement model, should be analyzed first to assure the validity and reliability of the model. To start with, the indicator loadings will be assessed to ensure that every indicator has a significant relationship with the corresponding latent variable. The factor loadings should exceed the minimum of 0.70 (Hair et al., 2019). Running the outer loadings shows multiple troublesome loadings of the indicators, as indicated in Appendix 2. Removing one indicator from the model is likely to affect the remaining indicator loadings. Therefore, indicators will be removed one by one, starting with the most troubling one. As a result, 13 indicators have been removed from the dataset. Most of the troubling indicators were related to the latent variable trust. Nevertheless, as indicated in Appendix 2, every remaining indicator has a factor loading of at least 0.70 and every latent variable has at least three related indicators.

Now that it has been concluded that all relationships between the indicators and the corresponding latent variables are significant, the reliability and validity of these constructs are to be checked. Table 1 shows the relevant measures for validity and reliability. The complete output of the SmartPLS software can be found in Appendix 2. Since the AVE value is above 0.50 for every construct, it can be concluded that the measures for all constructs are valid and measure what they ought to measure. Likewise, Cronbach's Alpha is above 0.70 for all constructs, meaning they are reliable as well. The measures can thus be used over time in other research.

| Construct | Cronbach's Alpha | Average Variance Extracted (AVE) |
|---|---|---|
| Brand strength | 0.901 | 0.772 |
| Customer's intention to cross-sell | 0.879 | 0.802 |
| Customer's intention to cross-sell | 0.864 | 0.786 |
| Control | 0.862 | 0.783 |
| Information sensitivity | 0.803 | 0.704 |
| Privacy concern | 0.902 | 0.773 |
| Personalization | 0.889 | 0.819 |
| Transparency | 0.863 | 0.709 |
| Trust | 0.877 | 0.673 |

*Table 1: Construct reliability and validity (Source: Processed data in SmartPLS).*

At last, the discriminant validity of the constructs is to be evaluated. Table 2 elaborates on the HTMT value per construct. Ideally, all these HTMT values would be <0.85, indicating that the indicators load best on the corresponding construct and there are no cross-loadings between constructs. This rule of thumb is met in every situation in this study, except for the correlation of transparency and control. The HTMT has a value of 0.879, indicating that the indicators for both control and transparency, will load on both constructs. However, as Hair et al. (2019) state, an HTMT value of 0.90 is acceptable in complex models. Besides, a correlation between the two constructs is not unexpected as Belanger et al. (2002) and Bleier et al. (2020) both indicate that transparency and control are often interrelated in practice. Therefore, the HTMT of 0.879 will be accepted in this case.

Based on the above evaluations on indicators loadings, construct reliability and validity, and discriminant validity, the measurement is assessed as satisfactory. As mentioned in chapter 3, the assessment of the measurement model will be succeeded by the assessment of the structural model. Hence, the structural model will be the next topic of this chapter.

| | **BS** | **CICS** | **CIU** | **CO** | **IS** | **PC** | **PE** | **TRA** | **TRU** |
|---|---|---|---|---|---|---|---|---|---|
| **BS** | | | | | | | | | |
| **CICS** | 0.469 | | | | | | | | |
| **CIU** | 0.651 | 0.745 | | | | | | | |
| **CO** | 0.423 | 0.401 | 0.372 | | | | | | |
| **IS** | 0.215 | 0.331 | 0.302 | 0.711 | | | | | |
| **PC** | 0.573 | 0.222 | 0.305 | 0.660 | 0.505 | | | | |
| **PE** | 0.609 | 0.557 | 0.792 | 0.372 | 0.304 | 0.338 | | | |
| **TRA** | 0.378 | 0.294 | 0.229 | **0.879** | 0.747 | 0.653 | 0.327 | | |
| **TRU** | 0.833 | 0.378 | 0.539 | 0.487 | 0.383 | 0.683 | 0.743 | 0.524 | |

*Table 2: Heterotrait-monotrait ratio (Source: Processed data in SmartPLS)*

### 4.2 Inner Model Analysis

The inner model, or structural model, dives into the relationships between the variables in the model (Hair et al., 2019). The interpretation of these results might be confused by the collinearity of the independent variables. Therefore, assessing the structural model will start with assessing this collinearity. As a rule of thumb, Hair et al. (2019) state that there is no reason for concern if the VIF value of the constructs is below 5. As indicated in Appendix 3, the VIF values for all constructs are below 5. Hence, the interpretation of results will not be troubled.

Next, the predictive power of the model is evaluated based on the $R^2$. The higher this value, with a maximum of 1, the higher the predictive power. Or in other words, the higher the value of $R^2$ the more variance in the endogenous variable can be explained by the model. Thus, table 3 indicates that the model has the highest predictive power for the construct of trust as 69.5% of the variance can be explained by exogenous variables in the model (i.e. personalization, control, transparency, information sensitivity, brand strength).

| **Endogenous variable** | **R Square** | **R Square Adjusted** |
|---|---|---|
| Customer's intent to cross-sell | 0.263 | 0.237 |
| Customer's intent to upsell | 0.492 | 0.474 |
| Privacy concern | 0.493 | 0.461 |
| Trust | 0.695 | 0.676 |

*Table 3: Model's predictive power (Source: Processed data in SmartPLS).*

| | Customer's intent to cross-sell | Customer's intent to upsell | Privacy concern | Trust |
|---|---|---|---|---|
| **Brand strength** | | | 0.185 | 0.549 |
| **Control** | | | 0.033 | **0.012** |
| **Information sensitivity** | | | 0.022 | **0.016** |
| **Privacy concern** | **0.003** | **0.008** | | |
| **Personalization** | 0.182 | 0.513 | **0.007** | 0.254 |
| **Transparency** | | | 0.034 | 0.048 |
| **Trust** | **0.000** | **0.001** | | |

*Table 4: Effect sizes (Source: Processed data in SmartPLS).*

| Hypothesis | Path | Original Sample | Sample Mean | Standard Deviation | t-value | p-value | Decision |
|---|---|---|---|---|---|---|---|
| H1 | PE -> CIU | 0.698 | 0.696 | 0.097 | 7.206 | 0.000 | Supported |
| H2 | PE -> CICS | 0.500 | 0.491 | 0.125 | 4.015 | 0.000 | Supported |
| *H3* | *PE -> TRU* | *0.340* | *0.336* | *0.087* | *3.925* | *0.000* | *Not supported, yet significant* |
| H4 | PE -> PC | 0.074 | 0.079 | 0.097 | 0.765 | 0.444 | Not supported |
| H5 | IS -> TRU | -0.094 | -0.100 | 0.072 | 1.317 | 0.188 | Not supported |
| H6 | IS -> PC | 0.143 | 0.171 | 0.128 | 1.123 | 0.262 | Not supported |
| H7 | CO -> TRU | 0.097 | 0.103 | 0.095 | 1.020 | 0.308 | Not supported |
| H8 | CO -> PC | 0.210 | 0.201 | 0.127 | 1.661 | 0.097 | Not supported |
| *H9* | *TRA -> TRU* | *-0.199* | *-0.206* | *0.098* | *2.020* | *0.044* | *Not supported, yet significant* |
| H10 | TRA -> PC | 0.215 | 0.209 | 0.127 | 1.686 | 0.092 | Not supported |
| H11 | BS -> TRU | 0.511 | 0.509 | 0.074 | 6.879 | 0.000 | Supported |
| H12 | BS -> PC | -0.382 | -0.378 | 0.098 | 3.884 | 0.000 | Supported |
| H13 | TRU -> CIU | -0.036 | -0.034 | 0.119 | 0.303 | 0.762 | Not supported |
| H14 | TRU -> CICS | -0.013 | -0.003 | 0.173 | 0.078 | 0.938 | Not supported |
| H16 | PC -> CICS | -0.063 | -0.056 | 0.136 | 0.461 | 0.645 | Not supported |
| H16 | PC -> CIU | -0.080 | -0.078 | 0.103 | 0.780 | 0.436 | Not supported |

*Table 5: Path coefficients direct effects (Source: Processed data in SmartPLS).*

| | Original Sample | Sample Mean | Standard Deviation | t-value | p-value |
|---|---|---|---|---|---|
| **BS -> PC** | -0.382 | -0.378 | 0.098 | 3.884 | 0.000 |
| **BS -> TRU** | 0.511 | 0.509 | 0.074 | 6.879 | 0.000 |
| **PE -> CICS** | 0.491 | 0.488 | 0.095 | 5.169 | 0.000 |
| **PE -> CIU** | 0.680 | 0.676 | 0.078 | 8.769 | 0.000 |
| **PE -> TRU** | 0.340 | 0.336 | 0.087 | 3.925 | 0.000 |
| **TRA -> TRU** | -0.199 | -0.206 | 0.098 | 2.020 | 0.044 |

*Table 6: Path coefficients total effects (Source: Processed data in SmartPLS).*

After, the effect sizes of the constructs are gauged. The associated measure for this is $f^2$ and it provides insights into the change of the predictive power when the construct is removed from the model. Generally, values for $f^2$ that >0.35 are considered to be strong effects. Values between 0.15 and 0.35 are considered to be moderate and the values between 0.02 and 0.15 are weak (Hair et al., 2019). The output of SmartPLS on this measure is included in Appendix 3. The modified table is presented in table 4. The strongest effects are presented in bold. Striking, in this essence, are the effects in bold. These are all <0.02, therefore even weaker than what is considered to be a weak effect. The elimination of trust from the model, for example, will have no impact on the predictive power of the model concerning the customer's intent to upsell and/or cross-sell.

At last, the significance of the relationships has to be taken into consideration to be able to draw conclusions from the results. This is done by the method of bootstrapping, as explained in the previous chapter. Appendix 3 contains the results of this bootstrap for the direct effects, total indirect effects, and total effects. As indicated, there are only significant ($p < 0.05$) effects to be found in the direct and total effects. Table 5 illustrates that hypotheses 1, 2, 11, and 12 are supported as they show significant relationships. The effects of personalization and transparency on trust are both significant, yet inversely related. Therefore, hypotheses 3 and 9 are not supported as they propose positive relationships. Additionally, those same six direct relationships are also significant when the total effects are being considered as illustrated in table 6.

# 5. Discussion

## 5.1 Conclusion

The aim of this research is to investigate the roles of trust and privacy concerns in the context of Artificial Intelligence. To do so, the Starbuck Deep Brew platform has been used as a real-life example to set the stage for this study and put the abilities and pitfalls of Artificial Intelligence in perspective. Hence, the following research question has been established:

*"What are the roles of trust of privacy concerns in the context of AI-enabled personalization?"*

To be able to come to a conclusion, the study commenced by providing an overview of the current state of the literature. This provided insights on both the topics of Artificial Intelligence, personalization, trust, and privacy as well as relationships between the constructs. Putting these insights in the context of the Starbucks Deep Brew app has resulted in the conceptual model as depicted in figure 2. To further investigate the proposed hypotheses, a survey has been conducted and the results of this survey have indicated that there are six significant relationships to be found in the original conceptual model. Figure 4 illustrates these found significant effects. As expected based on the hypotheses, the personalization aspect has a positive and direct relationship on both the customer's intent to upsell and cross-sell. Personalizing the marketing mix means personalizing not only delivering the right product at the right time, but it also means that it is done in the right manner. Starbucks has done this via the recommendations in their app. These are customized to the customer's needs and preferences, for which they increase the customer's intention to purchase the product. This increased intention to buy translates into the improved intention to upsell and/or cross-sell. These directs effects are the strongest effects found in the data, as depicted in Appendix 4. Thus, Starbucks' marketing objectives are indeed effectively achieved by personalizinh the in-app experience for customers. This is in line with both hypotheses 1 and 2 for which they are both accepted.

Next, this AI-enabled personalization has also a significant and positive effect on the consumer's trust in the brand. Notwithstanding that the found significant relationship is opposite to what was proposed in the third hypothesis. In other words, hypothesis 3 proposed a negative relationship between personalization and trust. However, the results have identified a significant, yet positive relationship. This means that an increase in the the level of personalization, results in an increase in the custumer's level of trust. A possible explanation for this significant relationship could be the fact that providing the right advice to customers, might influence the customer's perception of the brand (Aguirre et al., 2015; Ameen et al., 2021). As the customer is offered a coffee that is perfectly matched their preferences, they might perceive Starbucks as both more competent and less biased. Whereby their trust in the brand improves.

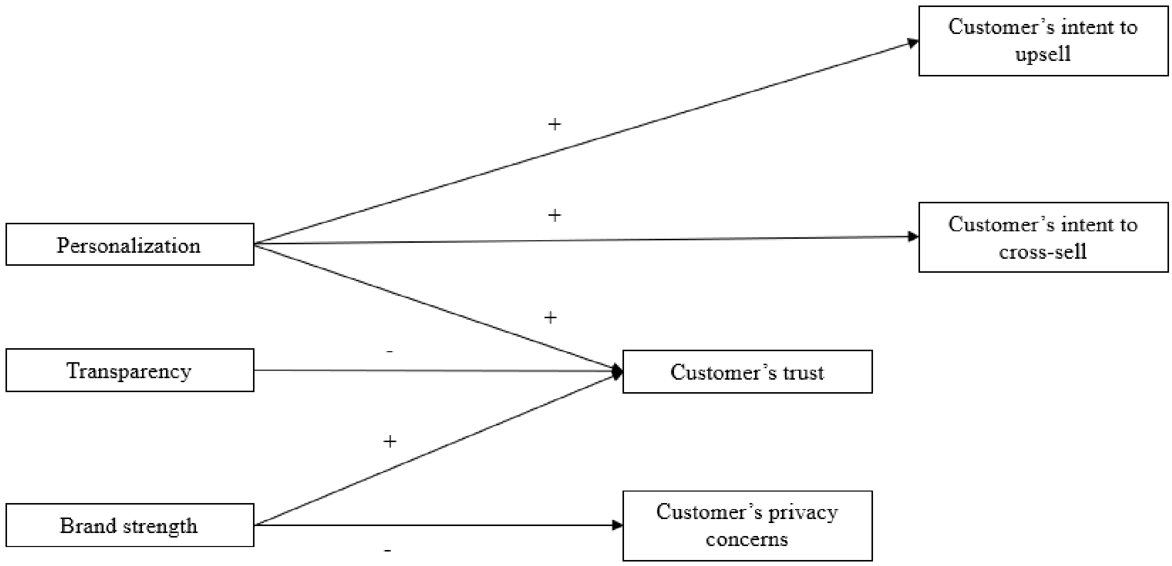

Figure 4 Significant results

Transparency is found to only have a significant effect on the customer's trust. Yet again, this relationship is opposite in nature to what has been proposed in hypothesis 9. Hypothesis 9 states that having insights into where the recommended coffee is coming from and how the AI algorithm works, was suggested to increase the customer's trust in Starbucks as a brand. However, this study shows the more transparent Starbucks is in its Artificial Intelligence applications, the less trusted the brand will be. Understanding the principles and applications of Artificial Intelligence concerning the Starbucks app might tap into a feeling of vulnerability and risk. Hidden patterns are to be found that relate to the customer's personal data. These patterns provide input for the recommended coffee for example, without any human intervention. As stated before, the lack of human intelligence will decrease trust in the recommendation (Ameen et al., 2021; Bleier et al., 2020; Wang & Benbasat, 2008). This might, too, resutl in a decreasing trust in the organization as well.

The last significant relationships are related to the constructs of brand strength. These results are in line with what has been proposed in hypotheses 11 and 12. Therefore, the brand 'Starbucks' is strong enough to function as a trust mark in uncertain situations. This trust mark is especially beneficial for improving the customer's trust in the brand. As illustrated in appendix 4, the construct of brand strenght holds the strongest relationship with the construct of trust. The privacy concerns, too, are minimized by the effects of Starbuck's brand strength. Customer expect a certain ground level of security from the organization. As a result, they feel confident that their data will only be used for the reasons it has been collected for and not been shared or used in different contexts (Bart et al., 2005; Hoyer et al., 2020).

Nevertheles, the concepts of trust and privacy were expected to play a mediating role between Artificial Intelligence and the customer's intention to upsell and/or cross-sell when ordering at Starbucks. These relationships, however, cannot be substantiated based on this study. As indicated in Appendix 4, the strongest effects path coefficients are found for the relationships between personalization and the customer's intention to upsell and/or cross-sell. Implying that the variance in these endogenous variables can mainly be explained by the direct effects of personalization. Based on this data, it can thus be stated that trust and privacy concerns do not significantly trigger a behavioral intent to order or not to order any (more) products in the Starbucks app. On the other hand, the AI-enabled personalized recommendations do so substantially.

### 5.2 Managerial Implications

Based on the results of this study, it could be beneficial for Starbucks to roll out its concept of the Deep Brew app to the Netherlands. Results show that the AI-enabled personalizations in the app will have positive effects on the sales and revenues of the company. The recommendations will result in a great customer's intent to upsell (i.e. a bigger coffee) their order and/or cross-sell (i.e. a cookie on the side). If done right, personalization can even result in more sustainable customer relationships as the trust in the company will improve. 'Right' in this context means that the whole marketing mix will be personalized to the customer, including the ways of communication for example and not only personalizing the recommended food or drink. Neverthless, time and effort must be devoted to finding the right degree of transparency in the firm's AI-related activities as transparency will presumably damage the consumer's trust in the company.

However, as the results show that Starbucks app is very successful in a way that it increases sales and revenue for the company substantially, it could be wise for Starbucks to investigate how to increase the number downloads of the app. Partly, this can be done by introducing the app in the Netherlands too. Nevertheless, a possible increase in downloads could also be sustained by promoting and marketing the app more heavily in the countries where it is already available. An increase in downloads, will result in an increase of opportunities to offer personalized offers to multiple customers. This will then result in an increase of these customer's intent to upsell and/or cross-sell when ordering in the app.

In general, these insights concerning Starbucks might be food for thought for marketing managers of different firms as well. Artificial Intelligence is not restricted to personalizing recommendations on food and drinks, it can be applied to endless branches and organizations. It will, however, open up possibilities to increase sales and revenues as is proven by the success of Starbucks.

**5.3 Limitations and future research**

Possibly the greatest limit of the research will be its sample size. Although it exceeds the minimum amount of respondents for the model to provide valuable insights, 87 valid answers is a relatively small sample. A small sample size will detriment the accuracy of the model. 10 out of the 16 relationships have not been significantly disclosed by the model. This could thus be a consequence of the limited sample. Unfortunately, the current study did have limited time and resources. It might therefore be relevant for future researchers, to conduct this research on a larger scale and investigate the (mediating) roles of trust and privacy concerns. As the accuracy of the model will increase, the predictive power will as well, resulting in more robust and detailed insights.

Secondly, this study has been focusing on the Starbucks case to narrow down the comprehensive topic of Artificial Intelligence. This has been a well-considered choice for this research as it reduces biases in the data. Presenting a clear case about a well-known organization, makes the opportunities and pitfalls of Artificial Intelligence more tangible. This will thus result in an increase of the respondent's understanding about the comprehensive topic of Artificial Intelligence. Therefore, this choice has increased the validity of the research. On the other hand, the results are very much focused on Starbucks. To be able to generalize the insights on trust and privacy to a larger scale, more research will be needed in different branches.

Lastly, the conclusions offer a possibly interesting road to follow in subsequent research to dig deeper in the role of trust in this context. As trust is mainly affected by the construct of brand strength in this model, it might be interesting to explore the effects of this trust on the personalization of Starbuck's recommendations. This relationship would close the circle as the recommendations have proven to substantially increase the sales and revenues of Starbucks. Therefore, exploiting the brand's strength, could improve the consumer's trust in the brand, which could increase either the number of downloads of the app or the acceptance rate of the recommendation, what would eventually lead to an increase in the customer's intent to upsell and/or cross-sell.

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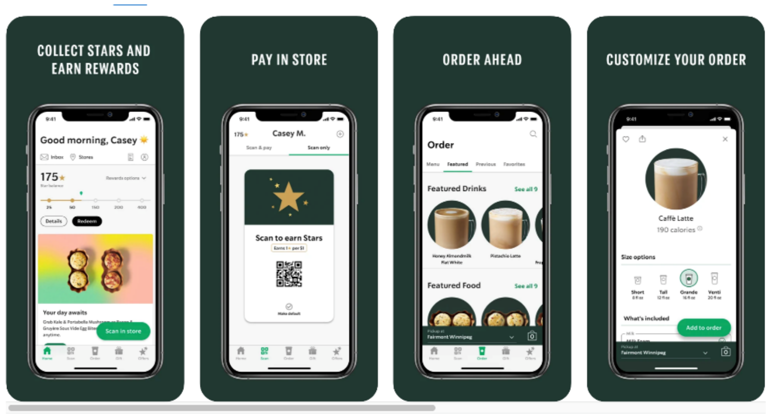
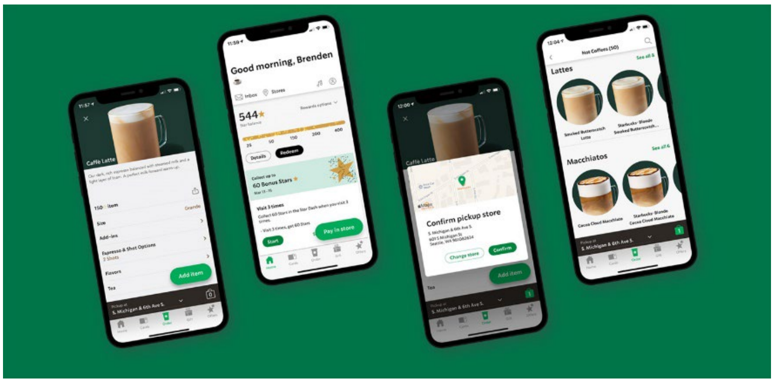
# Appendices

## Appendix 1 – Survey

***Dutch***

| | | |
|---|---|---|
| **Introduction** | | Alvast bedankt dat je deelneemt in dit onderzoek. Met het invullen van deze enquête help je mij om mijn masterscriptie af te ronden over personalisatie en kunstmatige intelligentie. Deze scriptie is onderdeel van de Master Marketing. Het invullen van de enquête kost je ongeveer 10 - 15 minuten van je tijd.<br><br>Lees de Starbucks casus alsjeblieft zorgvuldig door. Het is belangrijk dat je de casus volledig begrijpt om de bijbehorende vragen te kunnen beantwoorden. Jouw deelname is uiteraard anoniem en de data zal worden verwijderd na verwerking. Uiteraard mag je er op ieder moment voor kiezen om de enquête niet verder in te vullen.<br><br>Voor verdere vragen, voel je vrij om contact met me op te nemen.<br><br>Sanne van Rooij |
| **Case** | | Het was 1971 toen de koffieketen haar deuren opende in de straten van Seattle. Over de jaren heeft Starbucks zich verspreid over de hele wereld, is het 's werelds bekendste koffieketen en verwelkomt deze zij miljoenen klanten per week. Daarbij hebben zij maar één missie: "to inspire and nurture the human spirit – one person, one cup, and one neighborhood at a time" (Starbucks, n.d.). Met andere woorden, Starbucks heeft oog voor iedere klant als individu en probeert hen een unieke ervaring mee te geven. |

| | | |
|---|---|---|
| | | Vandaag de dag heeft Starbucks in verschillende landen al een app gelanceerd; Deep Brew, zoals Starbucks dit noemt. In deze app kun je als klant je bestelling online plaatsen en deze afhalen bij een Starbucks afhaalpunt. Zo hoef je bijvoorbeeld niet in de rij te staan wachten en is het bestellen van een koffie daarmee veel efficiënter. Zoals je bij de Albert Heijn bij iedere aankoop zegels spaart voor bijvoorbeeld koksmessen of bij de HEMA punten spaart voor kortingen, zo spaar je in deze app van Starbucks ook bonuspunten met iedere aankoop; de 'bonusstars'. In essentie is deze app een loyaliteitsprogramma waardoor jij iedere keer opnieuw geprikkeld wordt om een nieuwe aankoop te doen.<br><br>Maar deze app doet meer, het levert Starbucks namelijk waardevolle (en persoonlijke) informatie over jou. Stel je voor. Je wordt 's ochtends wakker op een zonnige, zomerse dag. Precies op het moment dat je zin krijgt in koffie, zie je een melding van Starbucks op je telefoonscherm verschijnen. Een suggestie van Starbucks: de koffie precies zoals jij hem lekker vindt met dit weer, mét dat ene lekkere croissantje. Je favoriete ontbijt en eventueel nog verder aan te passen zoals jij hem graag ziet.<br><br>Dat is geen toeval. Dat is de kunstmatige intelligentie van de Starbucks app die zijn werk doet. Onder andere de data over jouw eerdere aankopen, het weer, het tijdstip van de dag, jouw locatie, jouw smaakvoorkeuren en jouw besteedbare budget worden door de app opgeslagen. Op basis van deze data leert de app vervolgens wie jij bent als klant. Het is dus op basis van die data dat jij op precies het goede tijdstip de suggestie op je telefoon ziet verschijnen, die op dat moment precies bij jouw persoonlijke wensen aansluit. Met andere woorden, door gebruik te maken kunstmatige intelligentie |

| | | |
|---|---|---|
| | | kan Starbucks jouw ervaring in de app volledig personaliseren naar jouw persoonlijke wensen en voorkeuren. Dat ziet er dan ongeveer uit zoals hieronder afgebeeld.    |
| **Filtering questions** | FC1 | Ik begrijp wat kunstmatige intelligentie inhoudt in de context van de Starbucks casus. |
| | FC2 | Ik begrijp wat personalisatie inhoudt in de context van de Starbucks casus. |
| | FC3 | Ik begrijp de Starbucks casus over de Deep Brew app. |
| | FC4 | Ik woon (grotendeels) in Nederland. |
| **Demographic variables** | DV1 | Wat is uw geslacht? |
| | DV2 | Wat is uw geboortejaar? |
| | DV3 | Wat is ongeveer uw netto maandelijks inkomen? Denk eraan om alle verschillende inkomens mee te nemen. Waaronder salaris, uitkeringen, DUO, toeslagen, huur, etc. |

| | | |
|---|---|---|
| **Privacy concern** | PC1 | Ik zou me er oncomfortabel bij voelen om persoonlijke informatie te delen in Starbucks Deep Brew app, die gedreven wordt door kunstmatige intelligentie. |
| | PC2 | Ik zou me er oncomfortabel bij voelen om aankopen te doen via de Starbucks Deep Brew app, die gedreven wordt door kunstmatige intelligentie. |
| | PC3 | Ik zou me zorgen maken om het verlies van mijn privacy bij het gebruik van de Starbucks Deep Brew app, die gedreven wordt door kunstmatige intelligentie. |
| | PC4 | Ik zou me zorgen maken dat Starbucks mijn persoonlijke informatie voor andere doeleinden gebruikt als ik deze informatie deel met de Starbucks Deep Brew app, gedreven door kunstmatige intelligentie. |
| | PC5 | Ik zou me zorgen maken dat Starbucks mijn persoonlijke informatie met andere organisaties deelt. |
| | PC6 | Ik zou me zorgen maken dat Starbucks mijn persoonlijke informatie met andere organisaties deelt zonder mijn toestemming. |
| **Trust** | TRU1 | De Starbucks Deep Brew app, die wordt gedreven door kunstmatige intelligentie, komt als betrouwbaarder op mij over dan andere vergelijkbare apps die ik gebruik (bv. Albert Heijn, HEMA). |
| | TRU2 | De Starbucks Deep Brew app, die wordt gedreven door kunstmatige intelligentie, vertegenwoordigt een organisatie die zijn afspraken nakomt. |
| | TRU3 | Ik vertrouw de Starbucks Deep Brew app, die wordt gedreven door kunstmatige intelligentie. |
| | TRU4 | Ik vind de informatie in de Starbucks Deep Brew app, die wordt gedreven door kunstmatige intelligentie, als betrouwbaar overkomen. |
| | TRU5 | Ik heb vertrouwen in de aanbevelingen van de Starbucks Deep Brew app, die wordt gedreven door kunstmatige intelligentie. |

| | | |
|---|---|---|
| | TRU6 | Ik geloof dat de Starbucks Deep Brew app, die wordt gedreven door kunstmatige intelligentie, in staat zou zijn om mijn eisen en voorkeuren te begrijpen. |
| | TRU7 | Ik geloof dat de Starbucks Deep Brew app, die wordt gedreven door kunstmatige intelligentie, voldoende kennis heeft van koffie en bijgerechten. |
| | TRU8 | Ik geloof dat al mijn wensen en belangrijke eigenschappen van de producten in acht zouden worden genomen door de Starbucks Deep Brew app, die gedreven wordt door kunstmatige intelligentie. |
| | TRU9 | Ik geloof dat al mijn wensen op de eerste plek gezet zouden worden door de Starbucks Deep Brew app, die gedreven wordt door kunstmatige intelligentie. |
| | TRU10 | Ik geloof dat de Starbucks Deep Brew app, die gedreven wordt door kunstmatige intelligentie, mijn eisen en voorkeuren echt zou willen begrijpen. |
| | TRU11 | Ik geloof dat de Starbucks Deep Brew app, die wordt gedreven door kunstmatige intelligentie, onbevooroordeeld zou zijn in de aanbevelingen |
| | TRU12 | Ik beoordeel de Starbucks Deep Brew app, die wordt gedreven door kunstmatige intelligentie, als integer. |
| | TRU13 | Ik beoordeel de Starbucks Deep Brew app, die wordt gedreven door kunstmatige intelligentie, als betrouwbaar. |
| **Personalization** | PE1 | Ik zou waarde hechten aan de Starbucks Deep Brew app, die wordt gedreven door kunstmatige intelligentie, omdat het volledig gepersonaliseerd is naar mijn persoonlijke ervaringen. |
| | PE2 | Ik zou de Starbucks Deep Brew app, die wordt gedreven door kunstmatige intelligentie, waarderen omdat het mijn persoonlijke voorkeuren herkent en uit zichzelf mijn ervaring hierop aanpast. |
| | PE3 | De Starbucks Deep Brew app, die wordt gedreven door kunstmatige intelligentie, zou in staat zijn om mij te voorzien |

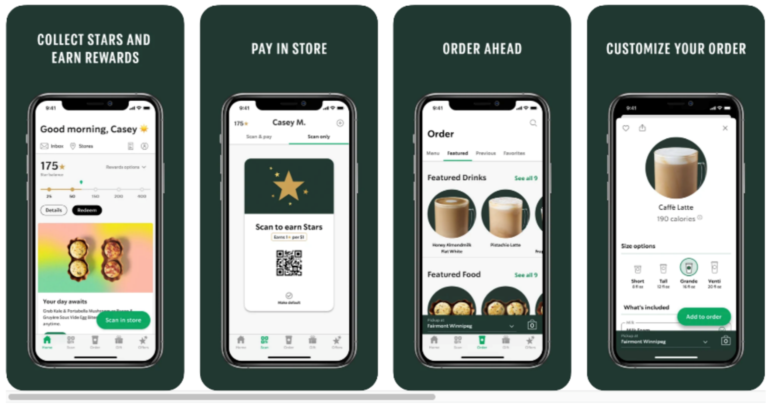
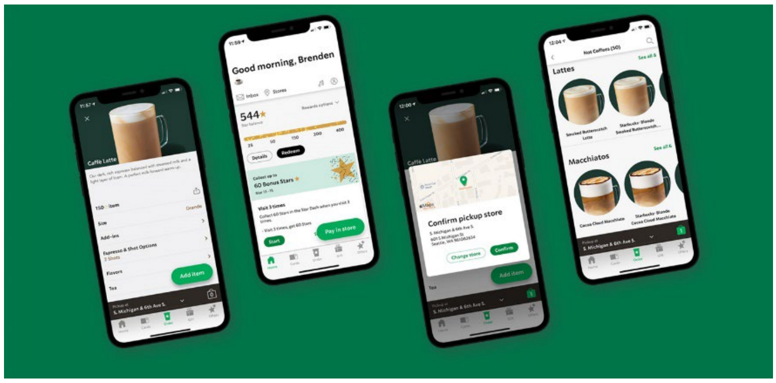
| | | |
|---|---|---|
| | | in mijn persoonlijke aanbevelingen op basis van mijn omgeving op dat moment. |
| **Information sensitivity** | IS1 | Ik zou het een probleem vinden dat de Starbucks Deep Brew app, die wordt gedreven door kunstmatige intelligentie, mijn financiële informatie (bv. besteedbaar inkomen) gebruikt. |
| | IS2 | Ik zou het een probleem vinden dat de Starbucks Deep Brew app, die gedreven door kunstmatige intelligentie, mijn persoonlijke informatie gebruikt. |
| | IS3 | Ik vind dat ik vaak persoonlijke informatie moet delen met apps in ruil voor de service die ze bieden. |
| | IS4 | Apps hebben de neiging om mij om gevoelige informatie te vragen zodat ik gebruik kan blijven maken van de service. |
| **Controle** | CO1 | Ik zou me zorgen maken dat ik de controle over mijn persoonlijke gegevens verlies als ik gebruik maak van de Starbucks Deep Brew app, die gedreven wordt door persoonlijke informatie. |
| | CO2 | Ik vind het doorgaans lastig wanneer ik geen controle heb over mijn persoonlijke data die ik prijsgeef in een app. |
| | CO3 | Ik vind het doorgaans lastig wanneer ik geen controle heb over de manier waarop mijn persoonlijke data wordt verzameld of gebruikt. |
| **Transparency** | TRA1 | Het is onduidelijk hoe mijn persoonlijke data wordt gebruikt door de Starbucks Deep Brew app, die gedreven wordt door kunstmatige intelligentie. |
| | TRA2 | Ik vind het doorgaans een probleem als het privacybeleid niet duidelijk en helder weergegeven wordt. |
| | TRA3 | Ik vind het doorgaans een probleem als ik er niet van op de hoogte ben hoe mijn persoonlijke gegevens gebruikt worden in apps. |
| | TRA4 | Ik vind het vervelend als apps mijn persoonlijke data nodig hebben maar niet toelichten hoe ze deze verzamelen, verwerken en toepassen. |
| **Brand strength** | BS1 | Ik voel me comfortabel bij Starbucks |

| | | |
|---|---|---|
| | BS2 | Starbucks is een kwalitatief goede organisatie. |
| | BS3 | De Starbucks Deep Brew app, die wordt gedreven door kunstmatige intelligentie, is in lijn met het beeld dat ik van het merk heb. |
| | BS4 | Starbucks is een eerlijke organisatie. |
| | BS5 | Ik vertrouw Starbucks. |
| | BS6 | Starbucks heeft belangstelling voor mij als klant. |
| **Customer intention to upsell** | CIU1 | Ik zou het aanbevolen product kopen. |
| | CIU2 | Ik zou mijn aanbevolen product nog verder upgraden (bv. een grotere koffie). |
| | CIU3 | Door de aanbevelingen zou ik sneller geneigd zijn om een product te kopen in de Starbucks Deep Brew app, die wordt gedreven door kunstmatige intelligentie. |
| **Customer intention to cross-sell** | CICS1 | Ik zou het aanbevolen bijgerecht kopen (bv. koekje) bij mijn koffie. |
| | CISC2 | Ik zou sneller geneigd zijn om in de app op zoek te gaan naar een extra product (bv. koekje bij de koffie). |
| | CISC3 | Door de aanbevelingen zou ik sneller geneigd zijn om een extra product (bv. koekje bij de koffie) te kopen in de Starbucks Deep Brew app, die wordt gedreven door kunstmatige intelligentie. |
| **Outro** | | Bedankt voor de tijd die je hebt genomen om deze enquête in te vullen. Hierbij heb je je steentje bijgedragen aan het afronden van mijn master scriptie.<br><br>Je antwoorden staan geregistreerd. Uiteraard gebeurt dit anoniem en wordt de data verwijderd na het verwerken ervan.<br><br>Mocht je verder nog vragen of opmerkingen hebben, dan kun je me bereiken op sanne.vanrooij@ru.nl |

*English*

| | | |
|---|---|---|
| **Introduction** | | Thank you in advance for your participation in this research. By filling out this questionnaire, you help me to finish my master thesis about personalization and artificial intelligence. This thesis is part of the MSc Marketing curriculum. Filling out the questionnaire will take about 10 – 15 minutes of your time.<br><br>Please read the Starbucks case carefully. It is important to fully understand the case in order to be able to answer the corresponding questions. Your participation is of course anonymous and the data will be deleted after processing. Of course, you are free to terminate the questionnaire at any point in time.<br><br>For any more questions, feel free to contact me.<br><br>Sanne van Rooij |
| **Case** | | It was 1971 when the coffee house opened her doors in the streets of Seattle. Over the years, Starbucks has spread around the world. It is now world's most famous coffee house and welcomes millions of customers per week. They have only one mission: "to inspire and nurture the human spirit – one person, one cup, and one neighborhood at a time" (Starbucks, n.d.). In other words, Starbucks pays attention to every individual customer and tries to give them an unique experience.<br><br>Today, Starbucks has launched an app in multiple countries. Deep Brew, as Starbucks herself calls it. In this app, a customer can place an order and collect it at a Starbucks pick up point. In this manner, one does not have to queue for example, what makes ordering a coffee much more efficient. |

| | | |
|---|---|---|
| | | As one can collect stamps at the Albert Heijn for professional knives for example or save for discounts at HEMA. Along these same lines, one can save 'points' in the Starbucks app with every order; the bonus stars. Essentially, this app is therefore a loyalty program that triggers the customers time and time again to buy a new product.<br><br>However, this app does a lot more. It provides Starbucks with valuable (and personal) information about you. Imagine. You wake up on a sunny summer morning and you see a notification of Starbucks popping up, exactly at this moment that you start to think about your morning coffee. Starbucks is suggesting a coffee to you: exactly the way you like it with this weather and with that one croissant you love so much. It is your favorite breakfast and is it even adjustable according to your personal preferences.<br><br>That is no coincidence. This is the work of the artificial intelligence, incorporated in the Starbucks app. Among others, data about your prior purchases, the weather, the time of the day, your geographic location, your taste preferences and your disposable income are being saved by the app. Based on this data, the app learns about you as a customer. It is thus due to this information that you are receiving your notification on your phone. In other words, Starbucks is able to personalize your experience in this app to your personal wishes and preferences due to artificial intelligence. This will look like presented below. |

| | | |
|---|---|---|
| | |    |
| **Filtering questions** | FC1 | I understand the concept of AI in the context of the Starbucks case. |
| | FC2 | I understand the concept of personalization in the context of the Starbucks case. |
| | FC3 | I understand the presented Starbucks case on the Deep Brew app |
| | FC4 | I (mainly) live in the Netherlands. |
| **Demographic variables** | DV1 | What is your gender? |
| | DV2 | What is your year of birth? |
| | DV3 | What is roughly your gross monthly income? Be sure to combine the total income such as wages or salaries, aliments, DUO, rents etc. |
| **Privacy concern** | PC1 | I would feel uncomfortable giving personal information on Starbucks' AI-driven Deep Brew app. |
| | PC2 | I would feel uncomfortable to shop via Starbucks' AI-driven Deep Brew app. |

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| | PC3 | I would be concerned about the loss of privacy when using the Starbucks' AI-driven Deep Brew app. |
| | PC4 | I would be concerned that when I give personal information to Starbucks' AI-driven Deep Brew app, that Starbucks would use this information for other reasons. |
| | PC5 | I would be concerned that Starbucks would sell my personal information to other companies. |
| | PC6 | I would be concerned that Starbucks would share my personal information with other companies without my consent. |
| **Trust** | TRU1 | Starbucks' AI-driven Deep Brew app appears to be more trustworthy that other apps I use (e.g. Albert Heijn, HEMA). |
| | TRU2 | Starbucks' AI-driven Deep Brew app represents a company that will live up to its promises. |
| | TRU3 | I trust Starbucks' AI-driven Deep Brew app. |
| | TRU4 | I consider the information on Starbucks' AI-driven Deep Brew app to be believable. |
| | TRU5 | I feel confident in the recommendations of Starbucks' AI-driven Deep Brew app. |
| | TRU6 | I believe that Starbucks' AI-driven Deep Brew app has the ability to understand my needs and preferences. |
| | TRU7 | Starbucks' AI-driven Deep Brew app has good knowledge about coffees and side orders. |
| | TRU8 | Starbucks' AI-driven Deep Brew app considers my needs and all important features of coffees and side orders. |
| | TRU9 | I believe Starbucks' AI-driven Deep Brew app puts my interests first. |
| | TRU10 | I believe Starbucks' AI-driven Deep Brew app wants to understand my needs and preferences. |
| | TRU11 | I believe Starbucks' AI-driven Deep Brew app provides unbiased product recommendations. |
| | TRU12 | I consider Starbucks' AI-driven Deep Brew app to be of integrity. |

| | | |
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| | TRU13 | Starbucks' AI-driven Deep Brew app is reliable. |
| **Personalization** | PE1 | I value Starbucks' AI-driven Deep Brew app as it is personalized for my personal experiences. |
| | PE2 | I value Starbucks' AI-driven Deep Brew app as it recognizes my personal preferences and personalizes my experiences itself. |
| | PE3 | Starbucks' AI-driven Deep Brew app has the ability to provide me with personalized deals that are tailored to my activity context. |
| **Information sensitivity** | IS1 | I am uncomfortable with the fact that Starbucks' AI-driven Deep Brew app uses my financial information (e.g. disposable income). |
| | IS2 | I am uncomfortable with the fact that Starbucks' AI-driven Deep Brew app uses my personal information. |
| | IS3 | In my opinion, I often have to share sensitive information with apps in exchange for their offered service. |
| | IS4 | Apps tend to ask me for sensitive personal information in order to obtain their services. |
| **Controle** | CO1 | I am concerned that I lose control over my personal data when I use Starbucks' AI-driven Deep Brew app. |
| | CO2 | It usually bothers me when I do not have control over the personal data that I provide on an app. |
| | CO3 | It usually bothers me when I do not have control or autonomy over decisions about how my personal information is collected and used. |
| **Transparency** | TRA1 | Starbucks' AI-driven Deep Brew app does not clearly inform me about how my data is used. |
| | TRA2 | It usually bothers me when online privacy policies do not have a clear and conspicuous disclosure. |
| | TRA3 | It usually bothers me when I am not knowledgeable about how my personal information will be used by apps. |

| | | |
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| | TRA4 | It usually bothers me when apps seek my personal data and do not disclose the way they collected, process and use this data. |
| **Brand strength** | BS1 | I feel comfortable with Starbucks. |
| | BS2 | Starbucks is a quality organization. |
| | BS3 | Starbucks' AI-driven Deep Brew app is consistent with the image I have of the brand. |
| | BS4 | Starbucks is a honest organization. |
| | BS5 | I trust Starbucks. |
| | BS6 | Starbucks shows interest in me as a customer. |
| **Customer intention to upsell** | CIU1 | I would purchase the recommended item. |
| | CIU2 | I would upgrade my recommended item (e.g. a larger coffee). |
| | CIU3 | I would be more inclined to buy an item in Starbucks' AI-driven Deep Brew app  due to the recommendations. |
| **Customer intention to cross-sell** | CICS1 | I would purchase an additional side order (e.g. cookie) if recommended. |
| | CISC2 | I would be more inclined to search for an additional product (e.g. cookie with the coffee) in the app. |
| | CISC3 | I would be more inclined to buy an item in Starbucks' AI-driven Deep Brew app  due to the recommendations. |
| **Outro** | | Thank you taking time to fill out this questionnaire. By doing so, you have contributed to the completion of my master thesis.<br><br>Your answers have been registered. Of course, this is done anonymously and the data will be deleted after processing.<br><br>In case you have any further questions or remarks, you can contact me via sanne.vanrooij@ru.nl. |

***Questions derived from***

| | | |
|---|---|---|
| **Filtering questions** | FC1 | Not applicable |
| | FC2 | Not applicable |
| | FC3 | Not applicable |
| | FC4 | Not applicable |
| **Control variables** | CV1 | Bart et al. (2005) |
| | CV2 | Bart et al. (2005) |
| | CV3 | Bart et al. (2005) |
| **Privacy concern** | PC1 | Bart et al. (2005) |
| | PC2 | Bart et al. (2005) |
| | PC3 | Ameen et al. (2020) |
| | PC4 | Hong et al. (2018) |
| | PC5 | Hong et al. (2018) |
| | PC6 | Hong et al. (2018) |
| **Trust** | TRU1 | Bart et al. (2005) |
| | TRU2 | Bart et al. (2005) |
| | TRU3 | Bart et al. (2005) |
| | TRU4 | Bart et al. (2005) |
| | TRU5 | Bart et al. (2005) |
| | TRU6 | Wang and Benbasat (2008) |
| | TRU7 | Wang and Benbasat (2008) |
| | TRU8 | Wang and Benbasat (2008) |
| | TRU9 | Wang and Benbasat (2008) |
| | TRU10 | Wang and Benbasat (2008) |
| | TRU11 | Wang and Benbasat (2008) |
| | TRU12 | Wang and Benbasat (2008) |
| | TRU13 | Ameen et al. (2020) |
| **Personalization** | PE1 | Ameen et al. (2020); Tyrväinen et al. (2020) |
| | PE2 | Ameen et al. (2020); Tyrväinen et al. (2020) |
| | PE3 | Tyrväinen et al. (2020) |
| **Information sensitivity** | IS1 | Bart et al. (2005) |
| | IS2 | Bart et al. (2005) |
| | IS3 | Hong et al. (2018) |

| | | |
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| | IS4 | Hong et al. (2018) |
| **Controle** | CO1 | Ameen et al. (2020) |
| | CO2 | Hong et al. (2018) |
| | CO3 | Hong et al. (2018) |
| **Transparency** | TRA1 | Bart et al. (2005) |
| | TRA2 | Hong et al. (2018) |
| | TRA3 | Hong et al. (2018) |
| | TRA4 | Hong et al. (2018) |
| **Brand strength** | BS1 | Bart et al. (2005) |
| | BS2 | Bart et al. (2005) |
| | BS3 | Bart et al. (2005) |
| | BS4 | Ameen et al. (2020) |
| | BS5 | Ameen et al. (2020) |
| | BS6 | Ameen et al. (2020) |
| **Customer intention to upsell** | CIU1 | Bart et al. (2005) |
| | CIU2 | Bart et al. (2005) |
| | CIU3 | Bart et al. (2005) |
| **Customer intention to cross-sell** | CICS1 | Bart et al. (2005) |
| | CISC2 | Bart et al. (2005) |
| | CISC3 | Bart et al. (2005) |

## Appendix 2 – Outer Model Analysis SmartPLS

*(Source: Processed data in SmartPLS).*

### *Outer Loadings before removing indicators*

| | BS | CICS | CIU | CO | IS | PC | PE | TRA | TRU |
|---|---|---|---|---|---|---|---|---|---|
| **BS1** | 0.816 | | | | | | | | |
| **BS2** | 0.865 | | | | | | | | |
| **BS3** | 0.348 | | | | | | | | |
| **BS4** | 0.862 | | | | | | | | |
| **BS5** | 0.898 | | | | | | | | |
| **BS6** | 0.669 | | | | | | | | |
| **CICS1** | | 0.873 | | | | | | | |
| **CICS2** | | 0.912 | | | | | | | |
| **CICS3** | | 0.900 | | | | | | | |
| **CIU1** | | | 0.881 | | | | | | |
| **CIU2** | | | 0.892 | | | | | | |
| **CIU3** | | | 0.887 | | | | | | |
| **CO1** | | | | 0.864 | | | | | |
| **CO2** | | | | 0.903 | | | | | |
| **CO3** | | | | 0.889 | | | | | |
| **IS1** | | | | | 0.650 | | | | |
| **IS2** | | | | | 0.905 | | | | |
| **IS3** | | | | | 0.764 | | | | |
| **IS4** | | | | | 0.798 | | | | |
| **PC1** | | | | | | 0.730 | | | |
| **PC2** | | | | | | 0.702 | | | |
| **PC3** | | | | | | 0.828 | | | |
| **PC4** | | | | | | 0.836 | | | |
| **PC5** | | | | | | 0.854 | | | |
| **PC6** | | | | | | 0.876 | | | |
| **PE1** | | | | | | | 0.915 | | |
| **PE2** | | | | | | | 0.919 | | |
| **PE3** | | | | | | | 0.881 | | |
| **TRA1** | | | | | | | | 0.789 | |
| **TRA2** | | | | | | | | 0.844 | |
| **TRA3** | | | | | | | | 0.885 | |
| **TRA4** | | | | | | | | 0.846 | |
| **TRU1** | | | | | | | | | 0.343 |
| **TRU10** | | | | | | | | | 0.591 |
| **TRU11** | | | | | | | | | 0.579 |
| **TRU12** | | | | | | | | | 0.780 |
| **TRU13** | | | | | | | | | 0.862 |
| **TRU2** | | | | | | | | | 0.609 |
| **TRU3** | | | | | | | | | 0.770 |
| **TRU4** | | | | | | | | | 0.641 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **TRU5** | | | | | | | | | 0.730 |
| **TRU6** | | | | | | | | | 0.684 |
| **TRU7** | | | | | | | | | 0.679 |
| **TRU8** | | | | | | | | | 0.632 |
| **TRU9** | | | | | | | | | 0.619 |

***Outer Loadings after removing troubling indicators***

| | BS | CICS | CIU | CO | IS | PC | PE | TRA | TRU |
|---|---|---|---|---|---|---|---|---|---|
| **BS1** | 0.821 | | | | | | | | |
| **BS2** | 0.882 | | | | | | | | |
| **BS4** | 0.893 | | | | | | | | |
| **BS5** | 0.914 | | | | | | | | |
| **CICS1** | | 0.874 | | | | | | | |
| **CICS2** | | 0.911 | | | | | | | |
| **CICS3** | | 0.900 | | | | | | | |
| **CIU1** | | | 0.882 | | | | | | |
| **CIU2** | | | 0.892 | | | | | | |
| **CIU3** | | | 0.886 | | | | | | |
| **CO1** | | | | 0.866 | | | | | |
| **CO2** | | | | 0.901 | | | | | |
| **CO3** | | | | 0.888 | | | | | |
| **IS2** | | | | | 0.908 | | | | |
| **IS3** | | | | | 0.787 | | | | |
| **IS4** | | | | | 0.818 | | | | |
| **PC3** | | | | | | 0.824 | | | |
| **PC4** | | | | | | 0.874 | | | |
| **PC5** | | | | | | 0.915 | | | |
| **PC6** | | | | | | 0.901 | | | |
| **PE1** | | | | | | | 0.915 | | |
| **PE2** | | | | | | | 0.920 | | |
| **PE3** | | | | | | | 0.879 | | |
| **TRA1** | | | | | | | | 0.784 | |
| **TRA2** | | | | | | | | 0.840 | |
| **TRA3** | | | | | | | | 0.889 | |
| **TRA4** | | | | | | | | 0.852 | |
| **TRU12** | | | | | | | | | 0.827 |
| **TRU13** | | | | | | | | | 0.899 |
| **TRU3** | | | | | | | | | 0.876 |
| **TRU4** | | | | | | | | | 0.730 |
| **TRU5** | | | | | | | | | 0.755 |

***Construct validity and reliability***

| | Cronbach's Alpha | rho_A | Composite Reliability | Average Variance Extracted (AVE) |
|---|---|---|---|---|
| **BS** | 0.901 | 0.911 | 0.931 | 0.772 |
| **CICS** | 0.879 | 0.921 | 0.924 | 0.802 |
| **CIU** | 0.864 | 0.867 | 0.917 | 0.786 |
| **CO** | 0.862 | 0.863 | 0.916 | 0.783 |
| **IS** | 0.803 | 0.918 | 0.877 | 0.704 |
| **PC** | 0.902 | 0.904 | 0.932 | 0.773 |
| **PE** | 0.889 | 0.892 | 0.931 | 0.819 |
| **TRA** | 0.863 | 0.863 | 0.907 | 0.709 |
| **TRU** | 0.877 | 0.894 | 0.911 | 0.673 |

## Appendix 3 – Inner Model Analysis SmartPLS

*(Source: Processed data in SmartPLS).*

### *Inner VIF values*

| | BS | CICS | CIU | CO | IS | PC | PE | TRA | TRU |
|---|---|---|---|---|---|---|---|---|---|
| **BS** | | | | | | 1.556 | | | 1.556 |
| **CICS** | | | | | | | | | |
| **CIU** | | | | | | | | | |
| **CO** | | | | | | 2.667 | | | 2.667 |
| **IS** | | | | | | 1.869 | | | 1.869 |
| **PC** | | 1.606 | 1.606 | | | | | | |
| **PE** | | 1.868 | 1.868 | | | 1.486 | | | 1.486 |
| **TRA** | | | | | | 2.685 | | | 2.685 |
| **TRU** | | 2.647 | 2.647 | | | | | | |

### $f^2$ values

| | BS | CICS | CIU | CO | IS | PC | PE | TRA | TRU |
|---|---|---|---|---|---|---|---|---|---|
| **BS** | | | | | | 0.185 | | | 0.549 |
| **CICS** | | | | | | | | | |
| **CIU** | | | | | | | | | |
| **CO** | | | | | | 0.033 | | | 0.012 |
| **IS** | | | | | | 0.022 | | | 0.016 |
| **PC** | | 0.003 | 0.008 | | | | | | |
| **PE** | | 0.182 | 0.513 | | | 0.007 | | | 0.254 |
| **TRA** | | | | | | 0.034 | | | 0.048 |
| **TRU** | | 0.000 | 0.001 | | | | | | |

*Path coefficients direct effects*

| | Original Sample (O) | Sample Mean (M) | Standard Deviation (STDEV) | T Statistics (\|O/STDEV\|) | P Values |
|---|---|---|---|---|---|
| **BS -> PC** | -0.382 | -0.378 | 0.098 | 3.884 | 0.000 |
| **BS -> TRU** | 0.511 | 0.509 | 0.074 | 6.879 | 0.000 |
| **CO -> PC** | 0.210 | 0.201 | 0.127 | 1.661 | 0.097 |
| **CO -> TRU** | 0.097 | 0.103 | 0.095 | 1.020 | 0.308 |
| **IS -> PC** | 0.143 | 0.171 | 0.128 | 1.123 | 0.262 |
| **IS -> TRU** | -0.094 | -0.100 | 0.072 | 1.317 | 0.188 |
| **PC -> CICS** | -0.063 | -0.056 | 0.136 | 0.461 | 0.645 |
| **PC -> CIU** | -0.080 | -0.078 | 0.103 | 0.780 | 0.436 |
| **PE -> CICS** | 0.500 | 0.491 | 0.125 | 4.015 | 0.000 |
| **PE -> CIU** | 0.698 | 0.696 | 0.097 | 7.206 | 0.000 |
| **PE -> PC** | 0.074 | 0.079 | 0.097 | 0.765 | 0.444 |
| **PE -> TRU** | 0.340 | 0.336 | 0.087 | 3.925 | 0.000 |
| **TRA -> PC** | 0.215 | 0.209 | 0.127 | 1.686 | 0.092 |
| **TRA -> TRU** | -0.199 | -0.206 | 0.098 | 2.020 | 0.044 |
| **TRU -> CICS** | -0.013 | -0.003 | 0.173 | 0.078 | 0.938 |
| **TRU -> CIU** | -0.036 | -0.034 | 0.119 | 0.303 | 0.762 |

*Path coefficients total indirect effects*

| | Original Sample (O) | Sample Mean (M) | Standard Deviation (STDEV) | T Statistics (\|O/STDEV\|) | P Values |
|---|---|---|---|---|---|
| **BS -> CICS** | 0.017 | 0.019 | 0.068 | 0.252 | 0.801 |
| **BS -> CIU** | 0.012 | 0.018 | 0.057 | 0.217 | 0.829 |
| **BS -> PC** | | | | | |
| **BS -> TRU** | | | | | |
| **CO -> CICS** | -0.014 | -0.013 | 0.048 | 0.302 | 0.763 |
| **CO -> CIU** | -0.020 | -0.020 | 0.035 | 0.590 | 0.556 |
| **CO -> PC** | | | | | |
| **CO -> TRU** | | | | | |
| **IS -> CICS** | -0.008 | -0.009 | 0.027 | 0.287 | 0.774 |
| **IS -> CIU** | -0.008 | -0.009 | 0.025 | 0.327 | 0.744 |
| **IS -> PC** | | | | | |
| **IS -> TRU** | | | | | |
| **PC -> CICS** | | | | | |
| **PC -> CIU** | | | | | |
| **PE -> CICS** | -0.009 | -0.003 | 0.072 | 0.128 | 0.899 |
| **PE -> CIU** | -0.018 | -0.020 | 0.050 | 0.366 | 0.715 |
| **PE -> PC** | | | | | |
| **PE -> TRU** | | | | | |
| **TRA -> CICS** | -0.011 | -0.012 | 0.035 | 0.309 | 0.757 |
| **TRA -> CIU** | -0.010 | -0.005 | 0.030 | 0.338 | 0.736 |
| **TRA -> PC** | | | | | |
| **TRA -> TRU** | | | | | |
| **TRU -> CICS** | | | | | |
| **TRU -> CIU** | | | | | |

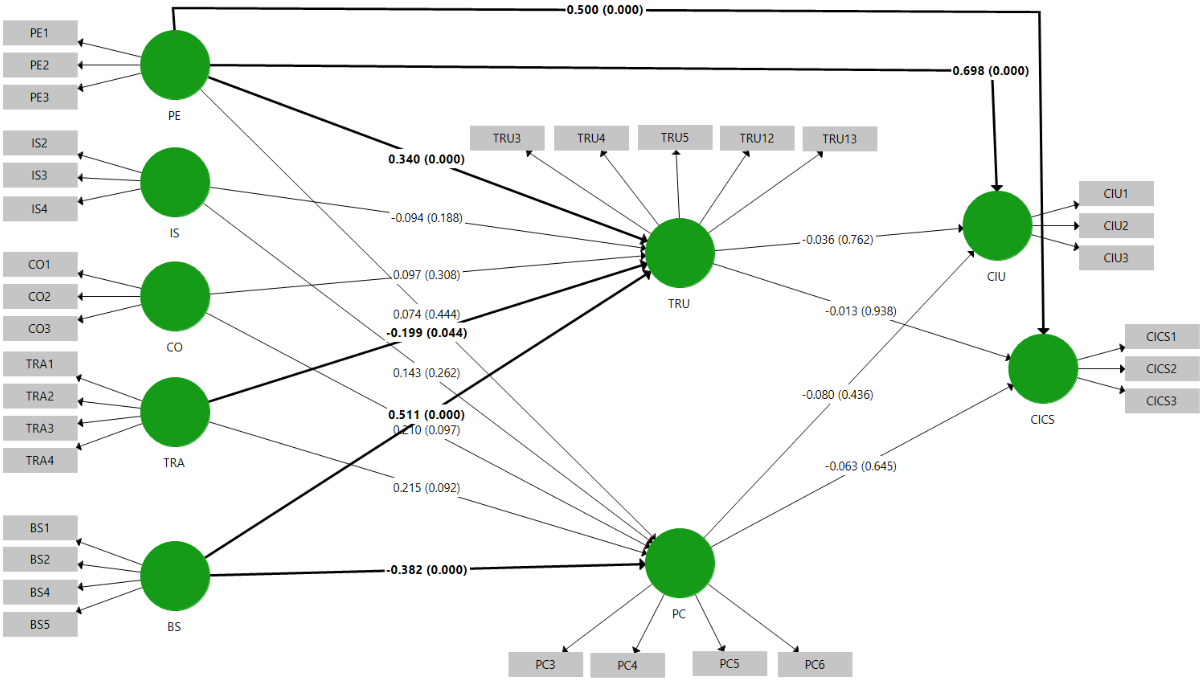
*Path coefficient total effects*

| | Original Sample (O) | Sample Mean (M) | Standard Deviation (STDEV) | T Statistics (\|O/STDEV\|) | P Values |
|---|---|---|---|---|---|
| **BS -> CICS** | 0.017 | 0.019 | 0.068 | 0.252 | 0.801 |
| **BS -> CIU** | 0.012 | 0.018 | 0.057 | 0.217 | 0.829 |
| **BS -> PC** | -0.382 | -0.378 | 0.098 | 3.884 | 0.000 |
| **BS -> TRU** | 0.511 | 0.509 | 0.074 | 6.879 | 0.000 |
| **CO -> CICS** | -0.014 | -0.013 | 0.048 | 0.302 | 0.763 |
| **CO -> CIU** | -0.020 | -0.020 | 0.035 | 0.590 | 0.556 |
| **CO -> PC** | 0.210 | 0.201 | 0.127 | 1.661 | 0.097 |
| **CO -> TRU** | 0.097 | 0.103 | 0.095 | 1.020 | 0.308 |
| **IS -> CICS** | -0.008 | -0.009 | 0.027 | 0.287 | 0.774 |
| **IS -> CIU** | -0.008 | -0.009 | 0.025 | 0.327 | 0.744 |
| **IS -> PC** | 0.143 | 0.171 | 0.128 | 1.123 | 0.262 |
| **IS -> TRU** | -0.094 | -0.100 | 0.072 | 1.317 | 0.188 |
| **PC -> CICS** | -0.063 | -0.056 | 0.136 | 0.461 | 0.645 |
| **PC -> CIU** | -0.080 | -0.078 | 0.103 | 0.780 | 0.436 |
| **PE -> CICS** | 0.491 | 0.488 | 0.095 | 5.169 | 0.000 |
| **PE -> CIU** | 0.680 | 0.676 | 0.078 | 8.769 | 0.000 |
| **PE -> PC** | 0.074 | 0.079 | 0.097 | 0.765 | 0.444 |
| **PE -> TRU** | 0.340 | 0.336 | 0.087 | 3.925 | 0.000 |
| **TRA -> CICS** | -0.011 | -0.012 | 0.035 | 0.309 | 0.757 |
| **TRA -> CIU** | -0.010 | -0.005 | 0.030 | 0.338 | 0.736 |
| **TRA -> PC** | 0.215 | 0.209 | 0.127 | 1.686 | 0.092 |
| **TRA -> TRU** | -0.199 | -0.206 | 0.098 | 2.020 | 0.044 |
| **TRU -> CICS** | -0.013 | -0.003 | 0.173 | 0.078 | 0.938 |
| **TRU -> CIU** | -0.036 | -0.034 | 0.119 | 0.303 | 0.762 |

## Appendix 4 – Model Outputs SmartPLS

*(Source: Processed data in SmartPLS).*

### *Inner model - bootstrap*




### *Outer Model – PLS Algorithm*