MASTER

Customer acceptance of interactive recommendation agents

the personalization-privacy paradox, perceived control and the influence of human-like appearance

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Customer Acceptance of Interactive Recommendation Agents: the Personalization-Privacy Paradox, Perceived Control and the influence of Human-Like Appearance

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Management Summary

The eminent e-commerce company Independer is developing a new self-service technology, an Interactive Recommendation Agent (IRA) to increase customer convenience and keep up with competition. The IRA has the task to provide interactive personalized product recommendations to the customer, executed in natural language in a chat interface. An IRA can have many benefits for the customers and thus the company. For the customer, enhancing interactive and personalization online can decrease information overload, and increase customer convenience, purchase intention and adoption. On the contrary, an IRA that recalls existing customer's personal information to provide a personalized product recommendation, that is personalization, can raise privacy concerns with the customer. Although many benefits are expected with an IRA for the company and its customers, realizing them is often a challenge. The purpose of this study is to provide strategic insight into relevant factors for customer acceptance of the IRA and its advice.

A key to meeting this purpose is to gain insight in customer perception in order to be able to understand the acceptance of the IRA and its advice. Previous literature states that finding explanations for customers' acceptance of the IRA technology is highly relevant and necessary to gain competitive advantage. Besides the acceptance of the technology, acceptance of advice is fundamental for the financial advisory function of the service agent. In addition, as the IRA is aimed to function as a hybrid service between the physical and online front office, it is crucial to know the appropriate appearance fits best for the acceptance of the customers. The factor of Human-Like appearance is taken into account. To extend knowledge on the underlying mechanism that influence customer acceptance of the IRA and its advice, the empirical cycle is followed to answer the main question:

To what extent do the Personalization-Privacy Paradox, Perceived Control and the level of Human-Like Appearance affect customer acceptance of the IRA its advice?

This research builds upon the existing theory of the Personalization-Privacy Paradox and the Theory of Planned Behavior. The trade-off between the benefits of enhanced personalization of a service and its associated privacy concerns is called the Personalization-Privacy Paradox. Furthermore, from research it is clear that consumers who are concerned that they have no control over the processing of their personal information perceive less control over the service encounter. As perceived control is known from the Theory of Planned Behavior to

be an important predictor of attitude and behavior, this factor is also taken into account. Moreover, research states that different decision making styles can influence consumers' attitude towards acceptance of technology, the Forrester's Self-Directedness Classification was used to test this. Additionally, the moderation effect of 'experience' and 'trust in automation' have been taken into account too.

To test the customer perception and acceptance for different levels of human-like appearance, an experiment set-up with a survey was used for collecting data. Three experimental groups where manipulated on different levels of human-like appearance: low human-like, moderate human-like and high human-like appearance. This was conducted with a video of a prototype of the IRA, publicized to a random selection of existing customers of Independer. The full respondents group consists of 189 customers. The data analysis was conducted mainly with Structural Equation Modeling.

The findings show that customers are not as sensitive in their privacy concerns as was expected in their experience with the IRA. It shows that IRAs that apply personalization when is asked for by the customer, does not induce privacy concern among customers and the benefits of a personalized service can be seized. Perceived personalization and perception of control have a strong positive impact on customers acceptance of the IRA and its advice. It is recommended to further investigate the different types of personalization, e.g. GPS tracking or browsing history, for its influence on customer acceptance. The results also show, that results on the three different levels of human-like appearance are found ambiguous and require further research. No difference in variance was found for the different customer decision making segments in this research.

Three main recommendations can be given. First, perceived personalized does not induce privacy concerns with customers experiencing the service agent. Furthermore, perception of personalization is important for the perception of control over the service encounter, which is of high importance to the customer acceptance of the IRA and its advice. Finally, it is recommended to investigate the appearance of the IRA and different customer segments further, with a larger respondents group and a real interactive setting.

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Abbreviations

AI	Artificial Intelligence
AVE	Average Variance Extracted
B2C	Business to Consumer
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CR	Construct Validity
CUI	Conversational User Interface
E-commerce	Electronical Commerce
EFA	Exploratory Factor Analysis
E-service	Electronical Service
HRI	Human-Robot-Interaction
IAT	Intelligent Agent Technologies
IFI	International Friction Index
IRA	Interactive Recommendation Agent
ML	Machine Learning
MR	Machine Reasoning
NLP	Natural Language Processing Tool
PNFI	Parsimonal Normed Fit Index
RMSEA	Root Mean Square Error of Approximation
SEM	Structural Equation Modeling
SPSS	IBM SPSS Statistics 25
SST	Self Service Technology
TAM	Technology Acceptance Model
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
VIF	Variance Inflation Factor

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1. Problem Definition

This chapter provides the empirical context of this study. It investigates the main problems of the company context and relates them to relevant frameworks in existing research, leading to the problem statement and the research questions. Finally, this chapter demonstrates the research approach, practical relevance and structure of this paper.

1.1. Empirical Context

This research is conducted within the context of Independer.nl NV (Independer). Independer is an eminent financial electronic commerce (i.e., e-commerce) company in the Netherlands. As an e-commerce company, their service is primarily web focused. Via the website of Independer, people can compare and contract available insurances in various fields, e.g., vehicle, health, and housing. Moreover, Independer has a strong financial advisory function in recommending products that best fit customers' individual situations. The main service of Independer is business to consumer (B2C) and focusses on transparency and marketing of products, sales and after sales. Presently, Independer's marketing strategy is shifting from product orientation towards improving long-term customer relationships and the optimization of online services.

In line with their marketing strategy, Independer aims to expand their online front office with a more interactive and personalized self-service technology (SST). The reason for this is the growing customer interest in service provision that is more convenient and personalized (Tuk, 2018). Self-service technologies "*allow customers to produce and consume services electronically without direct contact from firm employees*" (Meuter, Ostrom, Bitner & Roundtree, 2003, p. 899). SSTs can be for example ticket vending machines, self-checkout machines or online booking applications. Up to now, most online SSTs were not personalized, meaning they did not take into account the customers' individual needs. That is in great contrast with the physical front office, which consists of e-mail, phone and face-to-face communication and is more interactive and personalized (Wang, Harris & Patterson, 2011; Wang & Benbasat, 2005). Today, personalized SST's are achievable with advancements of Intelligent Agent Technologies (IAT) (Appendix 7.1) (Kojouharov, 2018).

To enhance personalized and interactive self-service on their website, Independer is developing an Interactive Recommendation Agent (IRA or 'service agent'). Marketers expect IRAs to increase perceived personalization, convenience and interaction in customer service

(Oxxio, 2018). The IRA operates in the form of a chat bot, embodying Human-Robot Interaction (HRI). In this context, the IRA's task is to provide an individual product recommendation to the customer, executed via natural language in a chat CUI (Conversational User Interface). For this reason, an IRA is an IAT that integrates both interaction and personalized SST online (Kojouharov, 2018). Therefore, the IRA is a hybrid service system, acting between the physical and online front office customer services (see Appendix 7.2). In addition, the service agent is always available and many customers can use it simultaneously. This makes it economically interesting for increasing availability of customer services. The IRA does not aim for a replacement of any existing services, but to increase online customer convenience, interactivity and personalized support. In conclusion, with an IRA the company intends to improve their competitive position in personalized online self-service, with the purpose to retain and attract customers for the longer term.

1.1.1 Problem Analysis

In reality, realizing the benefits of an IRA can be a challenge (Baker & Dellaert, 2016). As IRAs are an unfamiliar service for many customers, there is insecurity about their perception and level of acceptance of the IRA and its advice. For that reason, many companies are struggling with the implementation and acceptance of their service agents (Verelst, 2018). Likewise, Independer faces various challenges and uncertainties, related to customer perception and acceptance of their IRA.

An SST that enhances online personalization, that is, representing a customer's individual needs according to their personal information, encompasses many benefits for both the customer and the company (Komiak & Benbasat, 2012). In contrast, Independer recognizes that increased personalization may also raise privacy concerns among users. On the one hand, increased personalization means that customers have an easier process of decision making, and are more in control over the process because it is more convenient and "do-it-yourself" (Surprenant & Solomon, 1987; Wolfinbarger & Gilly, 2001). On the other hand, when customers are confronted with a system that already knows their personal data, they may perceive this as an invasion of privacy and experience increased privacy concerns. The trade-off in personalization and perceived privacy concern is called the Personalization-Privacy Paradox (Lee & Cranage, 2011). It is highly relevant for Independer to know to what extent this is true; to understand the trade-off for a positive perception of personalization versus privacy concern.

Furthermore, it is necessary to investigate how the Personalization-Privacy Paradox influences acceptance of the IRA. For the IRA to be useful as an online service, customer acceptance is essential. Acceptance can be defined as: "*the changes in individual attitudes, perceptions, and actions that lead them to try new practices, activities, or innovations that are different from their normal routines or behaviours"* (Kaldi, Aghaie, & Khoshalhan, 2008, p. 38). For Independer this means that customers are accepting the IRA technology as a new service channel. More specifically, besides the acceptance of the technology, acceptance of advice is fundamental for the financial advisory function of Independer. The task fulfilment of the IRA will fail, if its users do not accept also its product recommendations. This means that beside acceptance of the technological application, acceptance of its advice is fundamental for successful utilization of the IRA in Independer's financial advisory function. Stimulating customer acceptance of the IRA and its advice is important for the company to avoid unnecessary costs, as the production of the IRA involves high labour and technology investments (Lee & Allaway, 2002)**.**

To enhance both the benefits of personalization and the customer acceptance of the IRA, Independer also searches for the best visual appearance for the service agent. As the IRA is an IAT and in essence a robot, yet is to behave like a human advisor, the level of human-like appearance for the IRA is difficult to determine. Human-like appearance is defined by; "*the strategy of anthropomorphism through the use of human faces*" (Rizvanoğlu, Öztürk & AdIyaman, 2014, p. 165). For that reason, the company is looking for the optimal level of human-like appearance of the service agent.

1.2. Theoretical Relevance

Previous literature states that finding explanations for customer's acceptance of the IRA is highly relevant. A need for more in-depth understanding of drivers and barriers for consumers acceptance exists (Kumar, Dixit, Javalgi, & Dass, 2016; Xu, Luo, Carroll, & Rosson, 2010). The reason for this is that IRAs are still in development, and thus comprehensive theoretical frameworks for customer acceptance have yet to be developed (Verhagen & Feldberg, 2014; Xiao & Benbasat, 2007). In addition, no research has been conducted on the specific difference between the acceptance of technology and acceptance of advice (Kumar et al., 2016). That literature gap can be an interesting starting point to refine insight in customer acceptance of the IRA (Beer, Prakash, Mitzner, & Rogers, 2011).

Furthermore, research found that the shift in AI technologies for increased personalized shopping experience online, can lead to an increase in privacy concern for customers. Privacy concern in this context means the negative perception of the customer over personal data use by the company (Awad, Naveen ; Krishnan, 2006; Taylor, Davis, & Jillapalli, 2009). The Personalization-Privacy Paradox implies that the more personalized the agent is perceived, the higher the privacy concern for the customer can be (Surprenant & Solomon, 1987; Xu et al., 2010). Remarkably, in the research of Xu et al. (2010) users valued benefits of personalization twice as high as their perceived privacy concerns. This only counted for certain types of customers. Moreover, Zijlstra (2004) states that different decision making styles can influence consumers' attitude towards acceptance of technology, which can be investigated for IRAs.

In this context, perceived control is also considered for impacting customer acceptance. Known from the Theory of Planned Behavior, perceived control has been established as a key predictor for attitude and behavior of the customer in earlier research (Leotti & Ochsner, 2010; Schifter & Ajzen, 1985). In addition previous research showed that perceived control can mitigate between perceived personalization and customer attitude and behavior (Chen & Sundar, 2018). By combining these findings, perceived control can be seen as a relevant mediator between Personalization-Privacy Paradox and customer acceptance of the IRA.

Moreover, as the IRA is aimed to function as a hybrid service between the physical and online front office, it is crucial to know which level of human-like appearance has the best influence on the acceptance of the customers (Verelst, 2018). From literature there seems to be a tension field between increasing demand for personalized service and the actual influence of different levels of human-like appearance on customer's perception of personalization that is worth investigation (Ciechanowski & Przegalinska, 2018; Verhagen & Feldberg, 2014). It can be argued a high level human-like appearance does not fit the online context and thus mismatches the expectations of the customers, which can influence its evaluation negatively (Mori, MacDorman, & Kageki, 2012). In contrast, the customer should perceive the IRA as a skilled financial advisor, whereby a high degree of human-likeness might induce better response. However, the IRA is a robot and a low degree of human-like appearance might be appropriate to match the customers' expectation. In conclusion, in research there is a discrepancy on the influence of human-like appearance and perceived personalization, which requires further investigation (Beer et al., 2011; Wakefield, Baker, & Wang, 2011).

1.3. Problem Statement

Independer is uncertain about the influence of perceived personalization of the IRA on their customers' acceptance of the technology and its advice. Without customer acceptance the IRA cannot reach its full potential and the expected customer service improvements will not occur. Today the main challenges are the Personalization-Privacy Paradox and its effect on perceived control, and customer acceptance for different levels of human-like appearance. Hence, the problem statement reads as follows:

Independer is uncertain and previous research is inconclusive on the effect of the Personalization-Privacy Paradox on customers'perceived control, which affects customer acceptance of Independer's IRA and its advice.

1.4. Practical Relevance

This research aims to contribute to advanced insight in drivers for customer acceptance of an IRA. This is highly relevant today, as the online service agent field is gaining more and more attention. Use cases presented at the Chatbot Conference Utrecht show that the online service agent can reduce approximately 50 percent of call and live chat services, while increasing the amount of returning customers and their satisfaction (Hill-Wilson, 2018; Oxxio, 2018). The related cost reduction, by not having to scale up in costly human service personnel, though increasing service capacity, is estimated at approximately 66 percent (Hill-Wilson, 2018). Furthermore, it is stated that with an IRA the company can actually gain significant competitive advantage when it is strategically executed (Kumar et al., 2016). For these reasons, the relevance and potential benefits for insight in the customer acceptance process of the IRA is high.

1.5. Research Question

The purpose of this study is to provide strategic insight into relevant customer acceptance factors for the IRA of Independer. Verhagen and Feldberg (2014) emphasize that more research should be done specifically in the field of insurance products, because these kinds of products are perceived as riskier by the customer. For that reason the findings of this research aim at reducing the risk associated with the introduction of a new service agent for financial products and insurances. To realize the research purposes, this thesis follows the main question:

To what extent do the Personalization-Privacy Paradox, Perceived Control and the level of Human-Like Appearance affect customer acceptance of the IRA and its advice?

To support the main question, three sub questions are:

1. *What is the effect of perceived personalization on privacy concern?*
2. *How does the Personalization-Privacy Paradox affect perceived control?*
3. *How does perceived control affect the acceptance of the IRA and its advice?*
4. *To what extent do human-like appearance, and decision making segments influence customer acceptance?*

1.6. Research Approach

To answer the research questions this work follows the traditional sequence of the empirical cycle. In the first place, challenges are identified within the empirical context, in this case the company (Observation). In order to explain these observations, relevant existing theories are associated and generalizing hypotheses are formulated, illustrated by a conceptual model (Induction). The next step is formulating statistical methods for analysis (Deduction). Then data is collected and analysed according to the procedure that was described (Testing). Finally, findings are provided together with implications for future research (Evaluation) (Sprinz, 1998).

Search Strings

The induction phase of the empirical cycle has been done using the search engines Scopus, Worldcat and Google Scholar. The latter is only used for finding the highest citation papers, whereby the related journal's websites were always consulted for downloading papers. As the field of IRAs is a new and rapid developing field, the paper search was set from the year 2010. The snowball method has been applied whenever older papers are used, and also to find eminent auteurs in the field of IRA customer acceptance, personalization-privacy paradox or Human-Like appearance. In addition, 'recommendation agent' was always included with search terms to find the most relevant papers; avoiding 'chatbots' or general SST/ e-commerce papers.

1.7. Structure

The current chapter has provided the problem analysis and the relevance of the research, the following chapter discusses the context and existing literature, ending in a conceptual model. Chapter three describes the methods for data collection and statistical instruments, providing the operationalization of constructs in a list of items. Findings are presented in chapter four. The paper ends with a discussion, theoretical and managerial implications, and future recommendations: chapter five.

2. Theoretical Background

In the following chapter, different components of the research questions will be explained according to existing academic literature (see Figure 1). First, the scope and definition of service agents will be provided. Second, the main factors of research are introduced and defined, the Personalization-Privacy Paradox, perceived control and acceptance of the technology and advice. Furthermore, characteristics of the IRA, such as Human-Like Appearance as well as characteristics of the customer, such as decision making styles, are considered. Finally, the conceptual model is drawn together with the proposed hypotheses.

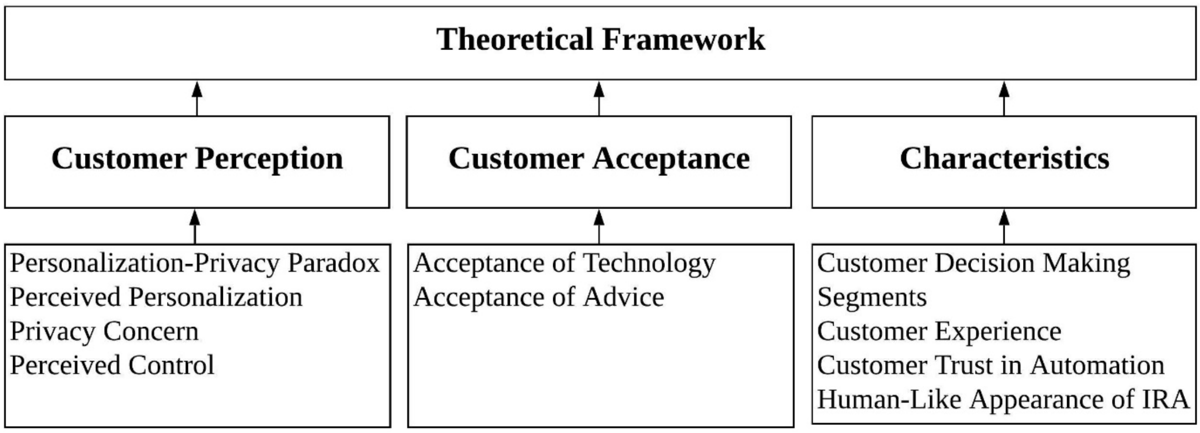


Figure 1: Theoretical Framework

2.1. Service Agents in E-commerce

Instead of a brick-and-mortar store interaction, customer purchasing and its assistance happens online more and more (Sousa & Voss, 2004). This is a result of the rapid rise of electronical commerce businesses (Xiao & Benbasat, 2007). The enormous growth of e-commerce makes it essential for companies to respond to the changing needs of the customer with innovation (Allen, 2017; Kumar et al., 2016). Today, this innovation and development emphasizes enhancing customer relationships, rather than primarily focussing on cost reduction through increased efficiency. Improving e-service, the "*provision of service over electronic networks*" (Rust & Kannan, 2003, p. 38), is therefore increasingly relevant, as it implies a customer centric approach (Doering et al., 2015; Rust & Kannan, 2003).

The maturing of artificial intelligent (AI) technologies, such as natural language processing (NLP) and machine learning (ML) made it possible to shift towards a new paradigm of e-services, like IRAs (Elhaney, 2018; Natanson, 2017; Rust & Kannan, 2003). Increased accessibility of data and power and storage improvements further enhanced the rise of robot-advice (Sesame & Mkhel, 2017). The IRA of Independer is based on Machine Reasoning (MR), rather than on ML. MR can be defined as: "*algebraically manipulating previously acquired knowledge in order to answer a new question"*(Bottou, 2011, p. 133). In practice, it means that in contrast to ML, the response by the IRA is not solely probabilistically calculated (i.e. ML) but is able to give relevant answers in unique and new situations, because of programmed reasoning skills (i.e. MR). MR and ML are essential in relation to the concept of intelligence (Bottou, 2011). To conclude, an interactive recommendation agent is part of Intelligent Agent Technologies (Kumar et al., 2016).

An IRA can, by means of natural language processing (NLP), interact in dialogue with the human customer. NLP can be defined as: "*enabling PCs to understand human language including slang, contractions, & pronunciations, and consecutively produce human-like dialogue and text*" (Grand View Research, 2017, p. 28). NLP is aimed to understand the intention of the language input, instead of only the information (i.e. words) itself (Crawford, 2018). There are different techniques to achieve this. Examples of these techniques are recognition of word patterns and synonyms, and estimation of the context (Eydman, 2018).

2.2. Definition of the IRA

It can be difficult to distinguish between types of online agents, as there are still no clear guidelines for naming different agents. The inconsistency in denomination is caused by the diversity of tasks, uses, methods and markets of the agents (Kumar et al., 2016). The complexity, lack of thorough understanding, and explorative phase of research, are also causes of inconsistency. In order to define the Independer's agent, an existing IAT taxonomy from Kumar et al., (2016) is used. It is a taxonomy of Intelligent Agent Technologies per marketing purpose and characteristic of the agent (Appendix 7.3). Identifying the autonomous decision-making component of the service agent, and its customer orientation, the term 'Recommendation Agent' fits Independer's agent best.

Additionally, Independer's recommendation agent strongly emphasizes interaction. To ensure this is immediately clear, the term Interactive Recommendation Agent is adopted, as in many other research papers (Su, Comer & Lee, 2008; Wang & Cole, 2016). IRAs can be defined as: "*software entities that carry out some set of operations on behalf of consumers, or another program, and provide shopping advice about what product(s) consumers should purchase based on their needs and/or preferences*" (Wang & Benbasat, 2005, p. 73). Although this may be a good denomination for the technology, agents with similar purpose are nominated differently. Other names can be: 'intelligent agent', 'service agent', 'recommendation agent', 'robo-advisor' or 'conversational agent' (Gnewuch, Morana, & Maedche, 2017; Haenen, 2017; Su, Comer & Lee, 2008). In this research only 'IRA' and 'service agent' will be used. Nevertheless, in general the feature of virtual human-robot-interaction and service provision are acknowledged in all the mentioned denominations.

According to literature, an IRA has benefits for the company and the customers. Several studies found support for customers being interested in using recommendation agents to acquire information, answer service questions and develop their decision making (Komiak, Sherrie, & Benbasat, 2006; McLean & Osei-Frimpong, 2017). It is an answer to the growing demand for human-like service, while firms spot opportunities to make it scalable and lower costs (Baker & Dellaert, 2016; McLean & Osei-Frimpong, 2017).Another important benefit is the full-time availability of such a personal service, that can also serve many customers simultaneously. This can reduce costs for the company (Gustavsson, 2005). Long-term profitability such as increased sales, customer repeat visits and retention are proposed (McLean & Osei-Frimpong, 2017; Sousa & Voss, 2004; Vijayaraghavan Albert, & Singh, 2011). An IRA is also expected to alleviate stress in customer service and customer journeys (Allen, 2017), shortening queues and waiting time for customers (chatbot.expert, 2018). Furthermore, companies have been adopting the service agents to increase customer satisfaction and the customer-company relationships (Al-Natour & Benbasat, 2015). Provided that these benefits are related to a successful IRA, the first step is to establish understanding of what brings its success. One way to do this is to research predictors of acceptance of the technology and its advice. The next chapter explains why the Personalization-Privacy Paradox is considered an important predictor for the acceptance of the IRA and its advice.

2.3. Personalization-Privacy Paradox

As explained earlier, the growth in technology and AI makes it possible for personalization to become an essential competitive factor for customer acquisition and retention (Taylor, Davis & Jillapalli, 2009; Tikka & Klaassen, 2017). Perceived personalization in this context can be defined as: "*the extent to which the RA understands and represents his or her personal needs*" (Komiak, Sherrie, & Benbasat 2006, p. 944). Here RA is used interchangeably with IRA, and 'his or her' refers to the user of the IRA. It becomes clear that an IRA in itself is already a great step in enhancing personalization in service provision (Murthi & Sarkar, 2003). The trend of increased personalization is becoming key in online service provision, for example as

Interactive Recommendation Agents (Gretzel & Fesenmaier, 2006; Li & Karahanna, 2015). Xiao and Benbasat (2007) suggest that the personalized context-sensitive content of the IRA is likely to enhance utility, and thus acceptance of the technology. Personalization decreases information overload which can affect customer convenience, purchase intention and adoption (Awad & Krishnan, 2006; Lee & Cranage, 2011; Li & Unger, 2012; Taylor et al., 2009). In practice, the aim is to increase personalization of its advice and give user-specific recommendations based on a customer's personal information. This kind of personalization depends on processing customers' personal information (Lee & Rha, 2016).

However, the IRA's access to the personal information needed for a personalized recommendation can raise privacy concerns with the customer. For example, the service agent can recall an existing customer's personal information to provide a personalized product recommendation. The storage and recall of personal information might be perceived as invasion of privacy. Therefore, the customer might be surprised by the display of their personal data by the IRA, influencing their privacy perception (Xu, Luo, Carroll, & Rosson, 2010). Privacy can be defined as follows: *"Privacy involves the protection of personal information - not sharing personal information collected about consumers with other sites (as in selling lists), protecting anonymity, and providing informed consent"* (Zeithaml, Parasuraman, & Malhotra, 2002, p. 364). In this research the term 'privacy concern' is adopted, as in Miltgen (2010). Privacy concern is considered a key dimension of customer perception of e-services. This was the conclusion of Zeithaml, Parasuraman and Malhotra (2002), after a broad review of existing literature on service quality delivery. Consequently, privacy concern is considered as a key determinant for IRA acceptance, as it is a modern customer need and important citizen right (Miltgen, 2010). The question remains to what extent the benefits of perceived personalization can outweigh privacy concern and what the influence is on acceptance of the IRA and its advice.

The trade-off between enhanced personalization of a service and its associated privacy concern is called the Personalization-Privacy Paradox (see Figure 2) (Lee & Cranage, 2011). On the one hand, various studies found that enhanced personalization outweighs privacy concern (Lee & Cranage, 2011; Li & Unger, 2012). The reason is benefit to the customer, for instance more precise and useful recommendations. This suggests that customers can be motivated to give personal information in exchange for the personalized advice (Xu et al., 2010). On the other hand, if consumers have the idea that they have no control over the processing of their personal information, the perceived personalization does not outweigh the concerns (Lee & Cranage, 2011). As a consequence, customers might be unwilling to accept the IRA and its advice (Awad & Krishnan, 2006). Earlier research showed that privacy concerns can also increase when the customer is not aware that this particular personal information was collected from them. This is called covert or implicit personalization, that is for example information from their browsing history or GPS tracking (Lee & Cranage, 2011). Finally, Awad and Krishnan (2006) state that the personalization-privacy trade-off can vary among contexts. As a result, it is argued that the implementation of personalization should be done cautiously, to avoid high privacy concerns (Montgomery & Smith, 2008).

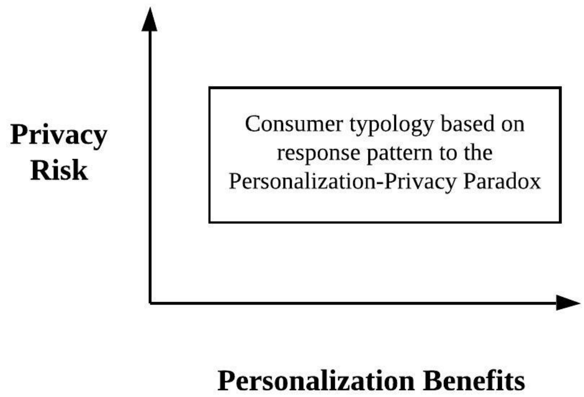


Figure 2: Personalization-Privacy Paradox (Lee & Rha, 2016)

Concluding, the perceived personalization can greatly benefit both the company and the customer, if the IRA is not raising too many privacy concerns. Therefore, measuring privacy concern associated with an IRA is essential for e-service companies to improve their customer service online (Yuan, 2011). Researching the current state of perception of both factors, as well as finding antecedents to reduce the privacy concern in the first place, will give insights into predictors of acceptance of the IRA and its advice (Lee & Cranage, 2011).

2.4. Perceived Control

Building further upon the framework of the Personalization-Privacy Paradox, the role of perceived control is examined. Perception of control is an essential factor for predicting humans attitude and behaviour (Leotti & Ochsner, 2010). Combining previous literature, it seems perceived control can strongly mitigate the Personalization-Privacy Paradox and customer acceptance of the IRA and its advice. This means that perceived control negotiates the relation between perceived personalization and privacy concerns and acceptance of the IRA and its advice. Within the context of SST, a common definition of perceived control is: " *the amount of control that a customer feels he/ she has over the process/outcome of a service encounter*"

(Bateson and Hui, 1987; retrieved from Fernandes & Pedroso, 2017). This means perceived control is the perception of having influence on the process.

What is interesting is that perception of personalization specifically can increase the perception of control in purchasing processes (Surprenant & Solomon, 1987). Also Chen & Sundar (2018) state that perceived personalization increases customer's perception of control over the service encounter, which is additionally an important factor for customer acceptance. A reason for this is that with personalized SSTs, customers require less assistance and have access to it at the moment of their choice, enhancing the perception of freedom and control (Wolfinbarger & Gilly, 2001). Perceived personalization can increase the perception of control over the service encounter, by the customer reaching its goals of receiving a personalized advice (Chen & Sundar, 2018). Conversely, previous studies show that customers perceived control is reduced if their privacy concerns increase, e.g. regarding their personal information (Awad & Krishnan, 2006; Taylor et al., 2009). This can result in a reduced willingness to share personal information with the medium, information that is essential for an IRA to give accurate recommendations (Bennett, Perrewé, Kane, Borgatti, & Performance, 2011). A way of decreasing the impact of privacy concerns can be information transparency or explicit personalization (Chen & Sundar, 2018).

In existing literature perceived control is a key factor in customer technology acceptance and intention to use an SST (Collier & Sherrell, 2010; Demoulin & Souad, 2016; Wang et al., 2011). Also Walker et al (2002) showed that perceived control is a critical element in customers' decision whether to use a self-service technology. For example, an essential part of perceived control is the customer's choice for the time of interaction or purchase, which is fundamental to an IRA (Wolfinbarger & Gilly, 2001). According to the Theory of Planned Behavior, perceived control is a key factor impacting the customer's future intention, attitude and use of the service agent (Collier & Sherrell, 2010; Pookulangara, Hawley, & Xiao, 2011; Schifter & Ajzen, 1985). Perceived control can also have significant influence on the service evaluation (Dabholkar, 2015). As a task gets more difficult (e.g. going through the self-checkout with many non-scannable items), a customer's perceived control over the task situation will be lower, and as a result the customer will not use the self-checkout in this situation regardless of prior attitude and intention (Wang et al., 2011). This is in accordance with findings of Lee and Allaway (2002). In conclusion, perceived control is included as an important factor to measure the attitude of the customer in the context of acceptance of the IRA technology and its advice.

2.5. Acceptance of the IRA technology and its Advice

Literature on technology acceptance is abundant. On the contrary, according to Komiak et al. (2006), no research measured the difference between the acceptance of IRA technology and the acceptance of IRA advice. This marks an opportunity for research, as this combination of customer acceptance is highly relevant for companies' IRAs. In this chapter, closely related terms are distinguished, followed by elaboration on the concepts of acceptance of technology and the acceptance of advice.

To understand the meaning of acceptance, the terms 'acceptance' and 'adoption' are first to be distinguished. Certainly both terms are concerned with the 'intention to use' a relatively unfamiliar technology and for that reason closely related, as a consequence they are easily confused. In this research the theory of Kladi, Aghaie & Khoshalhan (2008) is embraced, in which the term 'adoption' emphasizes the phase in which companies or individuals select the technology for use and competitive survival. It is considered an early phase of IT implementation (Appendix 7.4). Adoption can be defined as: *"the stage of technology diffusion in which an organization or individual decides to select a technology for use*"(Kaldi et al., 2008, p. 38). This is in contrast to acceptance, which emphasizes more on the perception and attitude of individual users in a later stage of the IT implementation process. Acceptance can be defined as: "*the changes in individual employee (user) attitudes, perceptions, and actions that lead them to try new practices, activities, or innovations that are different from their normal routines or behaviors"* (Kaldi et al., 2008, p. 38). For this research the company has already adopted the IRA, the question remains to what extent the users accept the technology and its advice.

For recommendation systems, recommending (i.e. giving advice) is their essential task. Therefore, for an IRA, measuring acceptance of its advice is similar to measuring acceptance of its technology. (Li & Karahanna, 2015). Acceptance of advice is researched in previous literature under different denominations. In the literature review on recommendation systems of Li and Karahanna (2015), this factor is called 'user acceptance of recommendations'. In other studies simply 'acceptance of advice' (Ronayne & Sgroi, 2018) or 'advice utility' (Goodyear, 2016) is used. 'Advice utility' insinuates actual use of the advice. Nevertheless in practice, it is often measured in the extent of acceptance versus rejection (Goodyear, 2016) or only in behavioural intention (Wang & Benbasat, 2005). For this study, that practice is considered too similar to the general definition of 'acceptance' (as mentioned in paragraph 2.3.1.). To be explicit about the what is being investigated, the terminology ‘acceptance of advice’ by Ronayne & Sgroi (2018) is used.

More than acceptance of advice, technology acceptance has been an eminent research topic in different scientific fields for many years. This results in much research attention going to existing models for measuring IRA acceptance of technology. The Technology Acceptance Model (TAM), the Theory of Reasoned Action (TRA), and the Theory of Planned behaviour (TPB) are well-known models in academic fields. All of these frameworks have already been researched in the context of web-based service (Luo, Chea, & Chen, 2011) and recommendation agents (Wang & Benbasat, 2005). As perceived control is considered to be an important predictor in the context of technology acceptance (see chapter 2.4), the Theory of Planned Behaviour is applied, where perceived control is one of three key predictors for customer attitude and behavior (Schifter & Ajzen, 1985). Within the current context, applying the TPB means assuming that the customer’s attitude, perception, and perceived control together predict behavioural intention, that is in this case acceptance of the technology and acceptance of advice.

2.6. Experience

In addition, according to existing literature, a customer’s experience can moderate positively to the increase of perceived control and over-all IRA evaluations (Bartneck, Kanda, Ishiguro, & Hagita, 2009). For example, Li & Unger (2012) found perceived personalization weaker for customers who had experience with service agents. It was also found that the related experience with IRA related privacy issues can strengthen the customers’ privacy concern in future IRA use (Smith, Dinev, & Xu, 2011). To increase understanding of the relationship between the Personalization-Privacy Paradox and perceived control for IRAs, the factor of experience is investigated for moderation effects.

2.7. Trust in Automation

Trust is apparent in many studies concerning adoption, and it is important to explore its influence in the context of the IRA as well. Previous literature show that personalization and user control are related with trust (Chen & Sundar, 2018; de Ruyter, Wetzels, & Kleijnen, 2000). Trust in automation is more specifically addressing the attitude of the customer towards the technology. To increase understanding of the relationship between the Personalization-Privacy Paradox and perceived control for IRAs, trust in automation will be investigated as moderator well.

2.8. Human-Like Appearance

To enhance both the benefits of personalization and the customer acceptance of the IRA, and meet customer expectations, the best visual appearance for the service agent will be investigated. Even though customers can be increasingly willing to accept online service agents (Verhagen & Feldberg, 2014), 35 percent of consumers acknowledge their biggest concern with them (i.e. online service agents) is losing the human touch (Hill-Wilson, 2018). After all, the online environment is by nature impersonal (Verhagen & Feldberg, 2014). This emphasizes the need for attention of human-like elements, to satisfy and attract the customer (McLean & Osei-Frimpong, 2017). Optimizing the IRA appearance for being like a skilled human advisor on the one hand, while on the other end applying a non-human dialogue is a challenge (Beer et al., 2011; Mori et al., 2012; Wakefield et al., 2011). Human-like appearance of a social agent in an HRI setting, can be defined as: "*the strategy of anthropomorphism through the use of human faces*" (Rizvanoğlu, Öztürk & AdIyaman, 2014, p. 165).

There seems to be disagreement in the literature about the most effective degree of human-likeness (Ciechanowski & Przegalinska, 2018; Strait, Vujovic, Floerke, Scheutz, & Urry, 2015). On the one hand, human-likeness can positively influence customer acceptance if designed successfully (Doering et al., 2015). Previous research proposes that every successful HRI agent is human-like, and can address different user groups (Beer et al., 2011; Doering et al., 2015). These studies mention human-likeness as significant explanation for customer's willingness to use a service agent (Van Den Berg, 2011). On the other hand, research findings propose that too much human-likeness can negatively influence customer evaluation (Beer et al., 2011). This inconsistency is acknowledged in the 'Uncanny Valley Hypothesis', investigated by Mori, MacDorman & Kageki (2012). The Uncanny Valley is a theory based upon this discrepancy between robot and human-like appearance preferences for customers. The theory states that from a certain degree onwards, the human-likeness results in negative customer evaluations, named 'the uncanny valley', pointing to the sudden decline of the curve (see Figure 3). As the relation between the IRA appearance and the customer behaviour is complex, it is worth further investigation (Minato, Shimada, Itakura, & Lee, 2008).

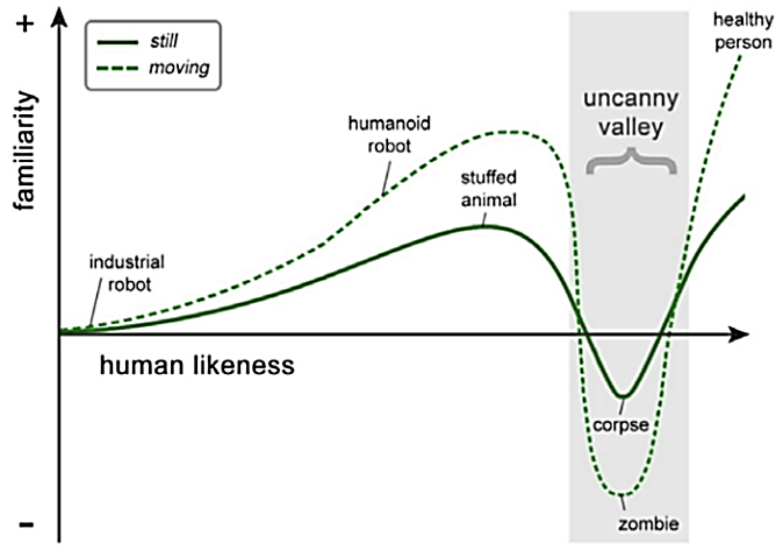


Figure 3: Uncanny Valley (source: Stein & Ohler, 2017)

2.9. Decision Making Segments

From research it is known different styles of decision making can also influence consumers attitude towards the IRA (Zijlstra, 2004). In the research of Xu et al. (2010) users valued benefits of personalization twice as high as their perceived privacy fears. However, they state their findings only accounted for certain types of customers. The study of Jackson, Yi and Park (2013, p. 154) state: "*A key factor that underlies user acceptance of IT has been suggested to be personality traits – individuals' predisposition to respond to stimuli across varying situations"*. In other words, different customer decision styles can have a relevant influence on the proposed associations to acceptance of the IRA. Subsequently, different customer groups based on decision style will be measured exploratory as moderators.

The different customer decision making segments are based on the Forrester Classification of Self-Directedness. The classification distinguishes four customer segments based on two dimensions: the extent of information gathering and the trust in advisors (see Figure 4) (Avramakis, 2011). This classification is specifically relevant in relation to accepting the IRA technology or its advice, as the preference for advisors is measured separately from customers' preference for technology or human-liken appearance. The Forrester Classification is often used in a financial advisory setting. For example, Danske Bank and Navy Federal Credit Union use this classification, and a derivative is used in the advisory statement of the national Dutch Authority of Financial Markets (Danske Bank, 2006; NFCU, 2017).

However, as the factors on both axis of the Forrester Matrix were never validated in the scientific field, two complementary, validated factors are chosen to represent the matrix. Namely, Sensitivity to Others' Opinions (depend on advisors) and Risk Taking Propensity (tenable to not gather information). Sensitivity to Others' Opinions can be defined as "*sensitivity to the opinions, wishes, and needs of other people; empathy; and capacity and need for intimacy and separation*" (Bekker & van Assen, 2006). Risk Taking Propensity can be defined by the inclination of someone to take chances. According to the characteristics of these groups, the acceptance of the IRA and its advice might be predicted differently for some groups. By comparing the groups against the model, this can be either confirmed or rejected.

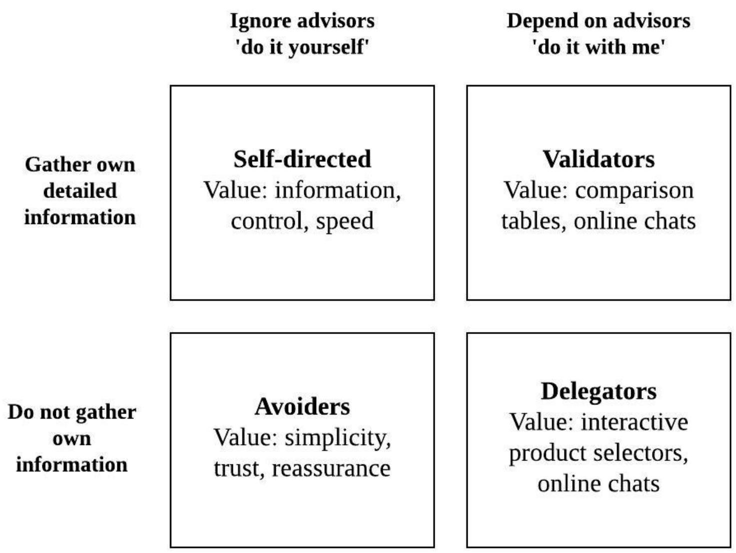


Figure 4: Forrester's Self-Directedness Classification

2.10. Research model

To be able to empirically measure the established relationships, hypotheses are provided. First, all hypotheses are explained and visualized in a conceptual model. Than, the control variables are given.

2.10.1 Hypotheses

A crucial component of an interactive marketing strategy is personalization (Montgomery & Smith, 2009).Without perception of personalization by the customer, the IRA is not the personal service agent it aims to be. However, research found an increase of personalization enhances the privacy concerns (Lee & Cranage, 2011). Today privacy concerns are highly relevant, regarding the increased attention for data breaches, for example the notorious data scandal between Cambridge Analytica and Facebook (Petrescu, 2018). Therefore, the association between perceived personalization and privacy concern will be tested with the following hypothesis:

H1. Perceived Personalization positively influences Privacy Concern.

It is also said that the perception of personalization can increase the perception of control, in purchasing processes (Surprenant & Solomon, 1987). This is especially the case with overt or explicit personalization (Appendix 7.5). Overt personalization indicates either the use of data that is explicitly collected and thus the customer has been aware of this process (Xu et al., 2010), or the explicit initiative of the customer for a personalized service (Chen & Sundar, 2018). This is the opposing term of covert personalization, which indicates using implicit factors for personalization (see Chapter 2.3). Overt personalization is by far more common in the use of financial advisory IRAs and mostly a positive influence on a customer's perceived control (Xu et al., 2010). To test this in the context for an IRA, the association between perceived personalization and perceived control will be tested with the following hypothesis:

H2. Perceived Personalization positively influences Perceived Control.

In contrast, Rust and Kannan (2003) emphasize the importance of the effect of privacy concern on perceived control in e-service settings, because of its negative effects on perceived service quality. Privacy concern is negatively associated with perceived control because of the tension between the customers' need to give information to the IRA and simultaneously wish to retain a control over their information and the process as a whole (Taylor et al., 2009). To test this in the context for an IRA, the association between privacy concern and perceived control will be tested with the following hypothesis:

H3. Privacy Concern negatively influences Perceived Control.

It is found that especially within SSTs customers are looking for control over the interaction with the company and their purchase process (Rust & Kannan, 2003). E-commerce companies already anticipate accordingly, for example with more product transparency or 24/7 customer service (Rust & Kannan, 2003). Particularly, a self-service technology in itself can enhance people's perceived control, providing that the service provider has a favourable design and coherent information presentation (Fernandes & Pedroso, 2017; Shi et al., 2016). According to the Theory of Planned Behaviour that was elaborated in chapter 2.5, perceived control positively enhances acceptance of technology. The benefits of perceived control, leading to more freedom for the customer, can lead to greater acceptance of the technology and of its advice. To measure this in the context of the IRA, where it is expected that perceived control influences customer acceptance directly, the hypothesis is as follows:

H4. Perceived Control positively influences Acceptance of Technology (a) and the Acceptance of Advice (b).

The appropriate level of human-likeness is also stated to be important to customer acceptance (Beer et al., 2011; Verelst, 2018). Especially since the IRA is to behave like a human advisor (Mhatre, Motani, Shah & Mali, 2016). According to the theory of the uncanny valley (elaborated in chapter 2.8), different levels of human-like appearance of a service agent can cause different effects on the customer perception. In accordance with the literature of Ciechanowski and Przegalinska (2018) the more the bot is perceived as unfamiliar, the more negative effects it will have on the users. For that reason, communicating personal information with an IRA that is perceived highly unfamiliar, i.e. not human-like, can induce negative perception on the customers in different ways. Therefore, it is important to measure to what extent the level of human-likeness can indeed moderate customer perception of an IRA. This will be exploratory investigated using the following hypothesis:

H5. Human-like Appearance significantly moderates the relationships in the model.

Finally, the factors of decision making segments are taken into account as exploratory moderators. The factors of risk taking propensity and sensitivity to others' opinions are expected to show differences in customer acceptance of the IRA and its advice. Also, to increase understanding of the relationship between the Personalization-Privacy Paradox and perceived control for IRAs, the factor of Experience and Trust in Automation, will be taken into account exploratory.

2.11. Conceptual Model

Following the hypotheses, the conceptual model illustrates dimensions that measure the dependent, or endogenous, variables Acceptance of Technology and Acceptance of IRA Advice (see Figure 5). The intervening variable, perceived control, allows a more detailed explanation of the relationship between the Personalization-Privacy Paradox and both acceptance variables. The Personalization-Privacy Paradox factors, personalization and privacy concern, are the independent, or exogenous, variables. This means it is assumed they partly explain the dependent variables. The interacting variables, or moderators (i.e. Experience, Trust in

Automation, Human-like Appearance and Decision Making Segments) are expected to affect the strength of the relationship between perceived control and the acceptance of the IRA and its advice.

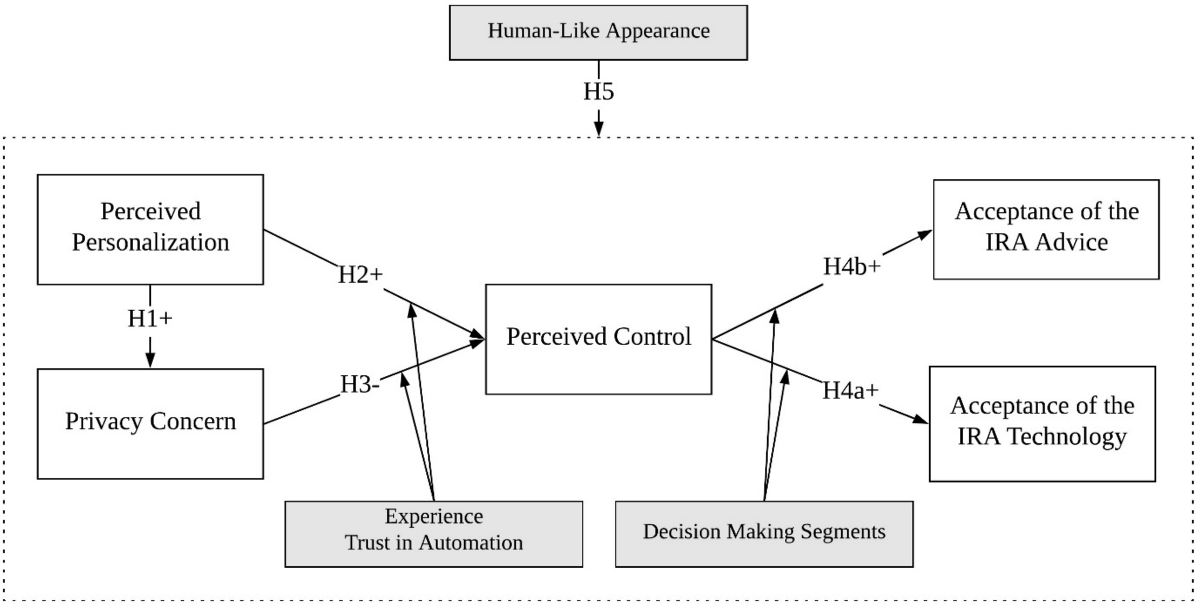


Figure 5: Conceptual Model

2.11.1 Control Variables

Control variables are included to be able to improve understanding of the relationship between the independent and dependent variables. As the control variables are expected to also have significant effect on measured relationships, they can be held constant during the experiment. This way the relative relationship of the key variables is understood better. From research, three demographic variables are found that should be held as control variables: age, gender and education level.

3. Methodology

The methodology of this study will be elaborated in this chapter. First, the general research method is described. Then, the specific experimental design of this study is elaborated, with special attention for manipulation and prototype design. Next, the composition of the survey is made clear, followed by results of the pretest. At last the final sample, analytical procedure and the data exploration are reported and explained.

3.1. Research method

To test how the IRA is accepted and perceived for different human-like appearance scenarios, quantitative research method is used for collecting data. The decision for quantitative methods has been based upon the possibility to pre-structure the gathering of data via the online platform (Boeije, ’t Hart, & Hox, 2009). Specifically, the researched variables could be established beforehand of data gathering, thus the questions for respondents could be standardized and best compared with quantitative methods. The quantitative method is characterized by medium to high amount of respondents, multi-explanatory variables and use of hypotheses for testing and elaborating (Sprinz, 1998). These characteristics manifest within this study.

Within the quantitative research method an experiment was executed. Boeije et al., (2009) argue that an experimental design for testing a causal relation between two or more variables, is a favourable method. To receive accurate data within the time and feasibility of the research, a post-test only design has been chosen. This means there is no test among the groups of respondents before the actual experiment. The benefit of this design is the increased external validity (both population and ecological validity), as the experiment is as close to reality as possible. The suggested experiment method is expected to improve reliability, with the aim to gain data as accurate as possible. Would a pre-test have been included, it could have induced a so called ‘test effect’ and ‘reactivity’, which means it might have led the respondents to focus on the topic of the questions in the pre-test while doing the experiment, which can influence and bias their responses (Boeije et al., 2009). Finally, it is a blind experiment, with only the researchers knowing which respondent is in which group.

3.2. Experimental Design

The experiment was conducted in three scenarios, for three experimental groups. The goal of the three groups is to be able to compare and analyse data for all scenarios. Figure 6 shows a sketch of the research design. The respondents were randomly distributed into three groups. This was executed via the CRM software of the company. Then, per group, all respondents received an e-mail with an invitation to collaborate with a research on the new e-service of Independer. Every group was exposed to the same e-mail text, though received a different link to go to their own experimental scenario (paragraph 3.5 explains this process in more detail). For the respondents, it was impossible to know the different scenarios.

The manipulation was done in the conversational flow of the expected IRA. A short movie showed a prototype IRA, with a case story of someone that contracted a home insurance some time ago via Independer. His housing situation changed and now he is interested if his insurance still fits his new situation, or if better options are available. The respondents were told to imagine being in the situation of this person while watching the dialogue. The dialogue in the prototype is for every group the same. When the prototype dialogue ends, the respondents can easily, on the same page, find a large yellow button to the survey questions that are presented in Table 1 (Appendix 7.12 for the web page with the prototype and button to the survey).

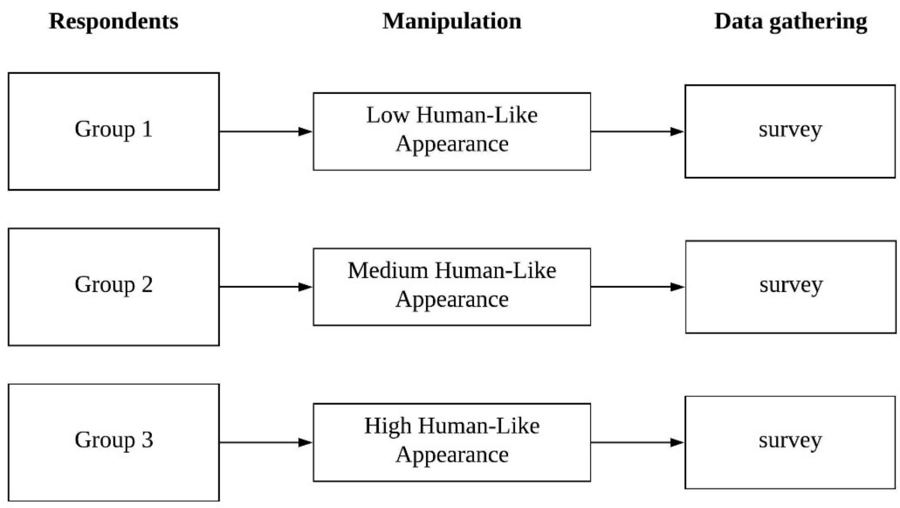


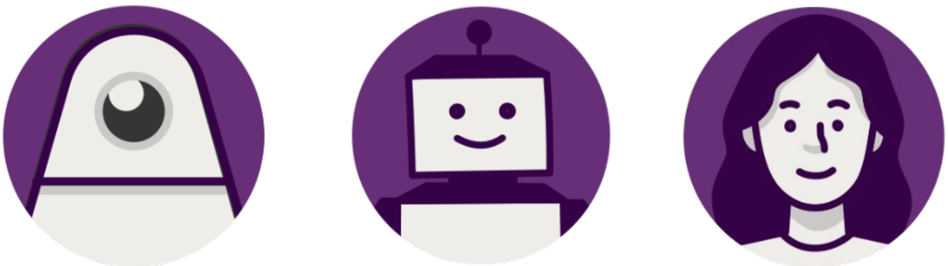
Figure 6: Experimental design

3.2.1 Manipulation Design

The experimental groups where manipulated on three different levels of Human-Like Appearance (see Figure 7). The choice for these three levels is based upon similar research that previously validated this manipulation method. Prakash & Rogers (2015) tested 3D robots for three different human-like faces. They tested on different user groups with the same division: low, moderate and high human-like embodiment (Appendix 7.6). Also the study of Strait et al. (2015), used the same division, with his own designs, for 3D robots. Also in this study, differences between the groups where found significant (Appendix 7.6).

In this study, the levels of Human-Like Appearance for the IRA have been developed in cooperation with the design department of Independer, in order to remain close to the company's design style and marketing strategy. The pictures have been created especially for this study (see Figure 7). The reason for this is that by testing pictures that are especially interesting for Independer in this context, the results of this study can be most relevant for the company. The manipulation pictures have purple elements by design, matching the branding strategy of Independer. From research it is known that low wavelength colours like purple, stand out less than high wavelength colours such as red (Lajos & Chattopadhyay, 2010).

The levels of Human-Like Appearance were tested in a standardized prototype that represented a conversation with the IRA (see example of placement in appendix 7.7). The existing company CUI design does not leave room for emphasizing the appearance, with the icons of the IRA being rather small. However, using the existing design can benefit the company in finding out to what extent their current design can affect its users. This also means the present setup might be less effective in finding strong results, than a design that emphasizes more on the IRA appearance, for example with larger icons. The existing setup is chosen to be able to recommend for their existing situation and the results being useful to different departments of the company.



a b c

Figure 7: The prototypes of Human-Like Appearances (a: non-Human-Like Appearance; b: medium Human-Like Appearance; c: high Human-Like Appearance)

3.2.2 Prototype Design

To be able to test the manipulation effect a standardized prototype of the actual IRA is designed. The conversation is to be based upon someone needing advice for his house insurance. This is because the IRA will be first launched for the existing customers with house insurances via Independer. Several steps were taken to create the most optimal prototype design for this purpose.

First the content of the dialogue was established by combining existing web forms and human-to-human customer service. A call center service expert was followed for 8 hours, whereby all relevant conversations were documented. Since some customers followed the whole web form, together with the call center service, the input was highly relevant to build a conversational flow of the house insurance purchasing and recommendation process. Second, the established conversation draft was shared and checked iteratively with the development team and the company's language specialists. This way, the right choice of words, understanding and correctness of advice was established. The final prototype dialogue, in Dutch, can be found in Appendix 7.8.

To standardize the experience of the customer, the dialogue would be shown in a video that is made in Sketch and Invision applications. Together with the design department the Independer style for chat dialogues was formatted to fit the requirements of desktop and mobile testing. By doing that, it was ensured that the customers would not be able to distinguish the prototype from a real IRA conversation, aside from not being able to intervene. This results in benefit such as a laboratory-like conditions and controllability of the interaction. Also, the standardized prototype that was used, could be made to an advanced version, showing the IRAs abundant capabilities to the respondents. With that, it was possible to show all personalization and Privacy Concern issues that are planned for with the real service agent.

The restrictions of using an actual IRA in the experiment, would have been the high probability experiencing different conversations per respondent. In addition, using a real beta version of the early IRA might induce a lot of errors or unforeseeable issues, making it difficult to control the encounters for comparison. For these reasons the standardized prototype is considered to be stronger and more reliable in comparing the specific elements of research between respondents.

3.3. Survey Design

Table 1 shows the operationalization of variables that were introduced in Chapter 2. Different scales have been used from existing literature, meaning that they are validated prior to this research. The scale of Perceived Personalization was constituted and some items were rephrased, to fit the specific context. In most cases, the words: ‘vendor’, ‘website’ or ‘product’, were transformed into the term ‘online assistant’. Using the word ‘interactive recommendation agent’ was expected to confuse the respondents and did also make items unnecessarily long and more difficult to comprehend. In addition, Independer did not have the intention to refer to the customers with the theoretical denomination ‘interactive recommendation agents’ in any case. At last all items were, together with intern the company’s language specialist translated into clear Dutch, for better understanding of the target group. The sources of the used items are supported here.

Acceptation of technology was measured with the three-item scale used by Komiak et al. (2006). The subject of recommendation agent was changed here into ‘service’, for all three items. The “Probability of Depending - Follow Advice” scale designed by Mc Knight et al. (2002) was used to measure ‘Acceptance of Advice’. Privacy Concern was measured by the four-item scale from Taylor et al (2009). Perceived control was adapted from the four-item scale of Koufaris (2002). Sensitivity to Others’ Opinion was used as a separable part of the autonomy scale of Bekker and van Assen (2006). The moderator personal innovativeness measured by a three-item scale of Liljander et al. (2006) and Risk Taking Propensity was measured by the scale of ‘Risk Taking Propensity’ scale of Bolton (2012). Experience was measured with a four-item scale, that was highly reliable in its use in the master thesis of Lichter (2017). The control variable trust in automation was measured by the three-item scale of de Ruyter et al. (2000).

Measures have been taken as much as possible, to secure the results from being biased or influenced. First, the instrumentation of data gathering is the online environment. This means there is no bias or influence from instructor to the participants. Moreover, regarding length of the survey, a Dutch news article states that people tend to be increasingly tired of evaluating services (Mulder & Jansma, 2018). This tiredness might affect the response rate. For that reason, the number of items that are necessary to generate data have been kept minimum, though above the threshold of 3 items per scale. To conclude, scale items were measured separately by a Likert scale from 1 to 5 in an online survey from (totally disagree to totally agree). The columns Factor Loading, AVE and CR will be elaborated in Chapter 3.8.

Construct		Item	Factor Loading	AVE	CR	Source
Acceptance of Advice	AOA1	If I had a product doubt, I would want to use this advice	*0.821*	*0.81*	*0.85*	(Mc Knight et al., 2002)
	AOA2	I would feel comfortable acting on the advice/information given to me by this service.	*0.983*			
	AOA3	I would not hesitate to use the advice/ information this service supplied me. [1]	-			
	AOA4	I would confidently act on the advice I was given.	*0.893*			
Acceptance of technology	AOT1	I would accept this advisor as an aid to help with my decision about which product to buy.	*0.849*	*0.68*	*0.85*	(Komiak et al., 2006)
	AOT2	I would be willing to let this service assist me in deciding which product to buy.	*0.822*			
	AOT3	I would accept this service as a tool that suggests to me a number of products from which I can choose.	*0.739*			
Personalization	PER1	The advice given by the online assistant is custom made with information of me personally	*0.788*	*0.75*	*0.90*	
	PER2	The online assistant recognizes me as a unique customer	*0.834*			
	PER3 -	The online assistant provides a generic and standardized advice which could be applied to anyone [1]	-			
	PER4	The online assistant makes time to get to know me personally	*0.677*			
Privacy Concern	PRC1	I would be concerned that information collected about me by a service like this could be misused	*0.81*	*0.55*	*0.71*	(Taylor et al., 2009)
	PRC2	I would be concerned that payment information used for purchases on a service like this could be stolen while being transferred	*0.86*			
	PRC3	I would be concerned about the privacy of personal information about me collected on via a service like this	*0.95*			
	PRC4	I would be concerned that personal information about me collected via a service like this could be used in a way I did not foresee	*0.89*			
Perceived Control		During the conversation with the online assistant:		*0.60*	*0.82*	*(Koufaris, 2002)*
	PEC1	I felt I was still in control over the process	*0.752*			
	PEC2 -	I felt uncomfortably [1]	-			
	PEC3	I felt calm	*0.725*			
	PEC4 -	I felt frustrated[1]	-			
Experience	EXP1	I have experience using a chatbot.	*0.917*	*0.59*	*0.81*	(Lichter, 2017)
	EXP2	I know how a chatbot works.	*0.970*			
	EXP3	I know how to communicate with a chatbot.	*0.682*			
	EXP4	I have experience with buying products through a chatbot.[1]	-			
Trust in Automation	TIA1	I would trust this interactive advisor	*0.857*	*0.77*	*0.93*	(de Ruyter et al., 2000)
	TIA2	I would trust that possible problems be solved well	*0.742*			
	TIA3	I would trust this interactive advisor less than other advisors	*0.712*			
Risk Taking Propensity	RTP1	I like to take risk by venturing into the unknown	*0.746*	*0.56*	*0.85*	(Bolton, 2012)
	RTP2	I am willing to invest a lot of time and/or money on something that might yield a high return	*0.605*			
	RTP3	I tend to act boldly in situations where risk is involved	*0.867*			
Sensitivity to Others' Opinion	STO1	I feel a strong need for other people's advice and guidance	*0,657*	*0.51*	*0,67*	(Bekker & van Assen, 2006)
	STO2 -	I am seldom inclined to ask other people's advice	*0,762*			
	STO3 -	When I take important decisions about my life, I leave other people's wishes and opinions out of consideration[1]	-			

Table 1: Constructs and Items

[1] Item was deleted before analysis (see Chapter 3.8.1)

3.4. Pre-test

Before the actual data sampling a premature test is executed among a small and select sample of family and friends. The reason for a premature test is twofold: on the one hand, it is a valuable moment for examining to what extent the experimental procedure is easy to follow to be able to find unexpected problems ahead of the main data collection. On the other hand, it is important for checking to what extent the proposed hypotheses are presented by actual data. The latter can provide a reason for reformulating the hypotheses, reconsidering the used factors of analysis or finding if the measure works at all.

The premature test was highly useful to point out the process errors. Unfortunately, the check for the effects of different levels of Human-Like Appearance was obstructed by the limitations found in the initial experimental set up. Because of a misunderstanding, the online survey program did not record the different respondents' groups by their different levels of manipulation and they could not be distinguished accordingly. On top of that the scale of Perceived Control was found to be malfunctioning in the survey and could not be interpreted for this sample. To conclude, crucial limitations of the initial process were found and solved, that secured for an uncorrupted final experimental setup.

Supported by a Cronbach Alpha analysis, the construct reliability was measured for the remaining scales. The Cronbach Alpha of all scales were > 0.69, meaning a high internal consistency of the scales. The scale of Trust in Automation alone was below this threshold ($\alpha = 0.243$). By a facial validity check, the third question seemed to be expressed unclear and was reformulated for the final data collection. With 35 respondents ($n = 35$) the Pearson Correlation Matrix was developed in IBM SPSS 25 (SPSS) (Appendix 7.9).

3.5. Sample and Respondents

The final sample of respondents consists of existing customers. They are targeted by having a house or car insurance at Independer, because the IRA will first be launched for these customer groups. The first call for participation of the research led to 60 respondents. Because more respondents are needed to compare the different scenarios of experiment, an incentive was added to the next batch of respondents that received an e-mail invitation to participate (see Appendix 7.10 for the first e-mail and Appendix 7.11 for the second e-mail). Response rates were 0.4% and 0.6% for the first and the second group.

The introduced incentive for the second group of respondents was a chance of one out of 25 vouchers of 10 euro from a large online retailer Bol.com. By the participants having a chance to win something, the research became part of small promotional gambling legislation, which resulted in some extra requirements. The company lawyer participated in making the public promotional conditions, which were posted on the experiment page, available for all participants (see Appendix 7.13). This incentive resulted in higher and demographically more diverse sample with 189 respondents (see Table 2). The diversity between samples shows in the check for equal variance with ANOVA. The significant results mean that the assumption of similar variation among the participants of the two sample groups is rejected (see Appendix 7.14). Then, the samples together were tested for representability of the actual population of Independer customers for age, gender and education level. Only for gender, there seems to be a small significant difference in variance. This will be compensated with a weighing score on gender in SPSS. The final sample demographically is shown in the tables below:

	Age						**Gender**	
	18-25	*26 - 35*	*36- 45*	*46 - 55*	*56 - 65*	*> 65*	*Vrouw*	*Man*
Group 1	10.1	42.0	13.0	18.8	5.8	10.1	58.0	42.0
Group 2	5.7	39.6	13.2	18.9	11.3	11.3	45.3	54.7
Group 3	13.4	25.4	14.9	26.9	11.9	7.5	32.8	67.2

	Education level						
	not willing to share	*None*	*Primary School*	*High School*	*Vocational education*	*Applied Sciences*	*University*
Group 1	2.9	0	0	4.3	29.0	44.9	18.8
Group 2	0	1.9	0	5.7	30.2	47.2	15.1
Group 3	1.5	0	0	16.4	31.3	32.8	17.9

Table 2: Demographic Characteristics of Final Sample in Percentages (n=189)

3.6. Methods of Analysis

To be able to answer the research questions, the hypotheses will be statistically tested with data from the final experiment. There are several ways to conduct data analysis. For main analysis, a combination of Confirmatory Factor Analysis (CFA) and Multiple Regression are often used for research with multiple dependent relationships. However, another option is CFA with Structural Equation Modelling (SEM). In contrast to the multiple regression analysis, SEM is more appropriate for complex models, meaning that they can have not only one, but multiple dependent variables in the research model (Hair, Black, Babin, & Anderson, 2014). In accordance with the selection criteria of Hair et al. (2014) CFA and SEM were performed for the main analysis of this study. SEM is known for its thorough confirmatory testing of a theory, with high standards of construct validity and reliability (Hair et al., 2014).

Before the main analysis, the data was prepared and explored in SPSS. Also, the scales were validated via Exploratory Factor Analysis (EFA), before the main analysis could take place. An overview of the data preparation and exploration is presented in the following paragraphs.

3.7. Data exploration

Before analysing the data with statistical tests, exploring the data is important to make sure the data can be used according to the presumptions of the test. Data preparation was conducted by recoding the survey output and reversing some questions. After doing so the data was explored for missing data, normality, outliers, linearity, multi-collinearity, representability of the population and common method bias.

Missing Data

The questionnaire software required the respondents to fill in all questions. Therefore, it was not possible to receive a survey that contained empty values. An analysis of frequencies and missing data confirmed this.

Normal distribution

Before checking for outliers, normal distribution of the data has to be confirmed. The central limit theorem states that any data sample above 30 units is normally distributed (de Vocht, 2010). Another way to check for normality is visually by means of qq plots. In SPSS qq-plots were analysed to check for normal distribution (see Appendix 7.15). Only education level seems to be too far from the normal distribution line. This is probably due to the items of “not willing to share”, which is not part of the education scale. The other variables meet the normal distribution criteria and further analysis can be done.

Outliers

Outliers do not follow the pattern of the main data and therefore must be removed. On the one hand this is important as outlier is being unrepresentative in the data. On the other hand, there is a concern that outliers can disproportional influence the analysis, even if it would be representative. To check for multivariate outliers the Mahalanobis Distance can be used. In SPSS the MD/q values that are bigger than 3 are considered outliers and were deleted from the data (Hair et al., 2014). Via this method one outlier has been removed.

Linearity

Linearity is an assumption for regression, which is part of the SEM analysis and is checked with scatterplots (Hair et al., 2014). The scatterplots in Appendix 7.16 include the straight line that depicts a linear relationship, showing linearity of the main variables can be assumed.

Multi-collinearity

Appendix 7.17 shows the test for multi-collinearity that was done in SPSS. The threshold for acceptable Variance Inflation Factor (VIF) is either a value below 5 or above 10 (Hair et al., 2014). As can be seen, the values for all items decline the existence of unwanted multi-collinearity.

Demographic check

As three groups of Human-Like Appearance are investigated, it is important to check for equal variance, to be able to compare the groups. The one-way ANOVA test in SPSS can prove that there is no significant difference in between the demographics for all groups, given the p-value being insignificant. The findings are insignificant, suggesting the groups may be compared in further analysis (Appendix 7.18).

Common Method Bias

Harman's one factor test can be used to check for common method bias. The rule of thumb is that one survey item should explain less than 50 percent of variance, in order to prevent the assumption of a common method bias (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). With an explained variance of 25 percent by one factor, and 67 percent for all survey items, the bias is considered unlikely.

3.8. Scale Validation

To validate the specified scales of the unobservable constructs, Explanatory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) is conducted.

3.8.1 Exploratory Factor Analysis

In theory EFA can be used to summarize and reduce data by variable selection with large surveys and unstructured items. In this case data reduction is not necessarily needed, because of the specific hypotheses and underlying theory pre-validating the scales used in this research. The EFA was primarily used for checking interrelated sets of items (cross loading) and validating the scale of Perceived Personalization. The cross loading check was especially important for the items that might be closely related, such as Acceptance of Advice and Acceptance of Technology. In factor analysis it is important to eliminate items that cross load over more than one factor (i.e. with loadings higher than 0.3 on one factor) (Hair et al., 2014).

The EFA was conducted with SPSS, exploring different rotation measures to create a better model interpretation. The final output can be seen in Appendix 7.19. After thorough consideration, the problematic variables (visualized in red) were eliminated for further analysis. The cross loading of items AOA3 and PEC4 were too high and thus deleted for further analysis. A few items did not load with their presumed factor and were eliminated also. This concerns Experience (EXP4) and Perceived Personalization (PER3), Perceived Control (PEC2) and Sensitivity to Others' Opinion (STO3).

Checking for construct reliability of the remaining items was conducted in SPSS, using Cronbach Alpha. The Cronbach alphas of the scales were all > 0.738, with exception of Perceived Control ($\alpha = 0.644$) and Sensitivity to Others' Opinion ($\alpha = 0.623$). In these cases however, no increase of the Alpha was possible by elimination of items. Considering the rule of thumb of $\alpha > 0.5$, the scales were kept for analysis. All remaining items will be used for their latent factors in further analysis.

Table 3 shows the Pearson Correlation Matrix, with the correlations between the established latent factors. In order to be able to check for moderation effects, parceling of items was considered. Parceling is taking the average of the sum items from different constructs to create a new construct. It can be an effective approach when constructs are measured by many items (Falk, Hammerschmidt, & Schepers, 2009). In contrast to the study of Falk et al. (2009), the number of items in this study is limited. As the parceling was considered for two-item constructs, this can easily lead to identification problems (Hair et al., 2014, p. 614). Under identification can, but not preferably, be compensated by other constructs with extra items. Unfortunately this structural model does not have an excess of items, leading to the SEM being unidentified when parceling. Instead of parceling, the technique of multiplication is conducted in the structural model according to theory of Hair et al. (2014).

	Acceptance of Advice	Acceptance of Technology	Privacy Concern	Personalization	Perceived Control	Risk Taking Propensity	Sensitivity To Others	Experience	Trust in Automation	Gender	Age	Edu. Level
Acceptance of Advice	1											
Acceptance of Technology	**0.645****	1										
Privacy Concern	-0.124	-0.134	1									
Personalization	**0.611****	**0.536****	-0.113	1								
Perceived Control	**0.523****	**0.469****	**-0.239****	**0.455****	1							
Risk Taking Propensity	0.094	0.026	0.032	0.138	0.071	1						
Sensitivity To Others	0.014	0.112	0.050	0.089	-0.001	-0.069	1					
Experience	0.135	**0.194****	-0.145	0.076	**0.375****	**0.250****	-0.070	1				
Trust in Automation	**0.765****	**0.602****	-0.211	**0.625****	**0.600****	0.091	-0.028	**0.183***	1			
Gender	0.081	0.074	-0.039	-0.002	0.002	**0.334****	-0.189	0.101	0.059	1		
Age	0.138	**0.175***	0.055	0.025	-0.045	-0.106	-0.001	-0.076	0.053	**0.214****	1	
Education Level	-0.043	0.019	-0.083	-0.140	0.023	0.117	0.023	**0.187***	-0.117	0.088	-0.161	1

***Significant at P<0.001; * Significant at P<0.05 (Two-tailed).*

Table 3: Pearson Correlation Matrix

3.8.2 Confirmatory Factor Analysis

In addition to the EFA a Confirmatory Factor Analysis was executed to check if the theoretically established items and constructs are also related via measurement. By that the CFA can confirm model fit, reliability and validity of the structure of established items and constructs (Hair et al., 2014). First the latent factors were standardized using SPSS. The CFA was conducted through a multi-dimensional measurement model in IBM AMOS Graphics 25 (AMOS) and can be seen in Appendix 7.20. It shows all relevant items and constructs, including independent and dependent variables, moderators and control variables.

A good absolute, incremental and Parsimonial model fit was found, which means there is no reason for modification, adding of new data or to refine the model. The model has a significant p-value, where insignificant is preferred, and the chi-squared is relatively high. The p-value and chi-squared are sensitive on sample size and complexity of the model. Considering the high complexity and many items in this model, these indicators can be assessed more lenient, thus other indicators, such as the Root Mean Square Error of Approximation (RMSEA), were also considered (Hair et al., 2014). The RMSEA is well below its threshold of < 0.08, resulting in a good absolute model fit (P-value 0.000; χ^2 457.40; RMSEA 0.064). The Comparative Fit Index (CFI), and International Friction Index (IFI) are above the threshold of > 0.90 and show a good incremental fit (CFI 0.96; IFI 0.937). At last the Parsimonal Normed Fit Index (PNFI) is assessed to check the model fit per estimated parameter. The value is higher than its threshold of > 0.60, meaning also a good Parsimonial fit was found (PNFI 0.683).

Validity was assessed by using the estimates from the measurement model. Factor loadings exceed the threshold of > 0.7 except for PER4 (0.677), RP2 (0.605) and EXP3 (0.682). In addition, communality of above > 0.5 is also achieved for all items except PER4 (0.453), RTP (0.366) and EXP3 (0.469). All Composite Reliability (CR) and Average Variance Extracted (AVE) values where found above the threshold of respectively > 0.7 and > 0.5, whereby the AVE exceeded its squared correlations (see Table 1), meaning good validity can be assumed (Fornell & Larcker, 1981). CR (ρC) and AVE were calculated in Microsoft Excel on using the following formulas:

$$\mathrm{AVE} = \frac{\sum_{i=1}^{k} \lambda_i^2}{\sum_{i=1}^{k} \lambda_i^2 + \sum_{i=1}^{k} \mathrm{Var}(e_i)} \qquad \rho_C = \frac{\left(\sum_{i=1}^{k} \lambda_i\right)^2}{\left(\sum_{i=1}^{k} \lambda_i\right)^2 + \sum_{i=1}^{k} \sigma_{e_i}^2}$$

4. Results

After factor analysis, structural models (i.e. full SEM) were used to test the hypotheses and interaction effects. As the model fit is assessed, the direction, size and significance of parameters may be used for conclusions and recommendations (Hair et al., 2014). This chapter gives a general overview of all the findings of statistical testing. In chapter 5.1 these findings are further elaborated.

4.1. Average Scores

The averages of respondents' answers provide a first impression of the respondents on the IRA. Table 4 shows the mean of the entire sample on measured scales. All factors are measured on a Likert-Scale from one to five. As can be seen the Acceptance of Technology of the IRA is well above average, Perceived Control and Experience likewise. Acceptance of Advice, Perceived Personalization and Trust are above average as well. Privacy Concerns are average. The standard deviation is roughly among 0.93 on all scales, except for Privacy Concern and Perceived Control (respectively 1.17 and 0.72). This means there is a larger variation in scores on Privacy Concern and in contrast, a smaller variation in scores on Perceived Control for the respondents.

Scale	n	Average	Standard Dev.
Acceptance of Advice	189	3.39	0.97
Acceptance of Technology	189	3.74	0.93
Perceived Personalization	189	3.14	0.92
Privacy Concern	189	2.63	1.17
Perceived Control	189	3.82	0.72
Experience	189	3.76	1.06
Trust	189	3.39	0.90

Table 4: Respondents' Average Scores

4.2. Mediation analysis

Before testing the main effects, the mediation effect of Perceived Control was investigated, to confirm the accuracy of its position in the model. In other words, the strength and direction of the mediation effect of Perceived Control were tested for the associations of Perceived Personalization and Privacy Concerns between both Acceptance of Technology and Acceptance of Advice.

Mediation is measured in four steps. Step 1 is confirming a direct and significant association between the independent variable and the dependent variable. If that is established, relationships between the independent variable and the mediator (step 2) and between the mediator and the dependent variable are established (step 3). These two findings are called the indirect path. Step 4 assesses the total effect, by adding the mediator to the direct effect model. If a reduction of the direct effect size is observable and still significant, there is partial mediation. This means that both, the direct and the indirect path, will be used in the full model. Full mediation occurs when the direct effect size is reduced and insignificant. This means only the indirect path will be used in the analysis. (Portland State University, 2018)

The mediation effect of Perceived Control is assessed in AMOS. Privacy Concern shows no significant direct effect on Acceptance of Technology and mediation will not be tested. The direct effect of Privacy Concern to Acceptance of Advice is negative and significant (β = -0.145; p-value < 0.1). The relation with the mediator is also significant (p-value < 0.05), as well as the relation between the independent variable (p-value < 0.001). By adding the indirect path, step 4, the direct path reduced in effect size and became non-significant (β = 0.064; p-value > 0.1). This means full mediation could be assumed.

Perceived Personalization is positively significantly related to Acceptance of Technology and Acceptance of Advice. The path between the mediator and the dependent variable are both significant as well. By measuring step 4 on Acceptance of Technology, the direct effect of Perceived Personalization is reduced and non-significant (β = 0.056; p-value > 0,1). This indicates full mediation. Regarding to step 4 of Perceived Personalization on Acceptance of Advice, the direct effect is reduced but still significant (β = 0.72; p-value < 0,1). This means that this relation is only partly mediated by Perceived Control.

4.3. Control Variables

Apart from mediation analysis, also the control variables are evaluated in the final model. Thus, the dependent variables age, gender and education level were added to investigate for a control function in the model. Variable age is defined in accordance with Independer's division of age groups (> 25, 26-35, 36-45, 46-55, 56-65, and > 65). Gender is dummy-coded by 0 (woman) and 1 (male) and education level is coded in 6 groups from low (0) to high (6). By adding all control variables, the model fit decreased significantly compared to the original structural model ($\Delta\chi^2$ 227-178 = 45, with p-value < 0.02). Furthermore, gender and education level show small and insignificant effect sizes (see Appendix 7.21). However, age significantly and positively relates to both acceptance constructs. By assessing the model fit only with age, there is no significant nor different model fit ($\Delta\chi^2$188–178=10, with p-value > 0,1). Therefore, only age is considered for further analysis.

4.4. Direct Effects

The full SEM is conducted in three models, direct effects and interaction effects for the whole respondent group, followed by a multi-group analysis. In this paragraph the first two models are explained. First the model fit and explained variance is shortly elaborated.

A good over all model fit is found (see Appendix 7.22). The χ^2 is medium to low, which is preferred (χ^2 227.8). The Comparative Fit Index (CFI) and International Friction Index (IFI) are above the threshold of > 0.90 and show a good incremental fit (CFI 0.934; IFI 0.935). The Parsimonal Normed Fit Index (PNFI) is higher than its threshold of > 0.60 (PNFI 0.714). The R^2 for both outcome variables results in a medium explained variance (R^2 = 0.667 and R^2 = 0.694). This means, 66.7 percent of variance for Acceptance of Advice is explained by the model, with Perceived Control and Age being significant predictors. Furthermore, 69.4 percent of variance is explained for Acceptance of Technology by the same model, with Perceived Control and Age being significant predictors.

Table 5 below shows the results of the full SEM. The table individually represents all associations and their effect size (β/beta weights or standardized regression weight) and Standard Error (S.E.) in columns. The reason for separately addressing these associations in rows is based upon the sequential nature of the structural model, making a matrix visualization too inefficient.

Hypothesis one is rejected by the model. The results of Perceived Personalization on Privacy Concern reject proposition H1 that Privacy Concern is positively affected by Perceived Personalization (β = -0.138; p-value < 0.1). Instead, hypotheses two, three, four ‘a’ and ‘b’ are supported with the model. Perceived Personalization significant and positively effects Perceived Control, demonstrating affirmation for hypothesis 2 (β = 0.742; p-value < 0.001). Privacy Concern is significant and negatively related to Perceived Control, accepting hypothesis 3 (β = -0.128; p-value < 0.1). Perceived control was found to be significantly associated with Acceptance of Advice (β = 0.654; p-value < 0.001) and Acceptance of technology (β = 0.814; p-value < 0.001), supporting both hypotheses 4a and 4b.

					Model 1 *Direct Effects*		Model 2 *Interaction effects*	
		Predictor		**Dependent variable**	β	S.E.	β	S.E.
Main effects	*H1*	Perceived Personalization	→	Privacy Concern	**-0.138***	0.11	-0.135	0.10
	H2	Perceived Personalization	→	Perceived Control	**0.742*****	0.11	**0.722*****	0.11
		Perceived Personalization	→	Acceptance of Advice	0.189	0.18	**0.206***	0.17
	H3	Privacy Concern	→	Perceived Control	**-0.128***	0.05	**-0.126***	0.06
	H4a	Perceived Control	→	Acceptance of Technology	**0.814*****	0.13	**0.810*****	0.12
	H4b	Perceived Control	→	Acceptance of Advice	**0.654*****	0.22	**0.645*****	0.19
Control		Age	→	Perceived Control	-0.075	0.05	-0.073	0.06
		Age	→	Acceptance of Technology	**0.250*****	0.06	**0.250****	0.06
		Age	→	Acceptance of Advice	**0.185****	0.06	**0.185****	0.06
Interaction		Risk Taking Propensity *x* Perceived Control	→	Acceptance of Technology			-0.011	0.04
		Risk Taking Propensity *x* Perceived Control	→	Acceptance of Advice			-0.031	0.05
		Sensitivity to Others' Opinion *x* Perceived Control	→	Acceptance of Technology			**-0.129****	0.04
		Sensitivity to Others' Opinion *x* Perceived Control	→	Acceptance of Advice			**-0.142****	0.05

****Significant at P<0.001; ** Significant at P<0.05; *Significant at P<0.1.*

Table 5: SEM results model 1 and 2

4.4.1 Interaction Effects

Apart from hypotheses testing, interaction effects are investigated, in search for significant customer decision making characteristics or experience on the established associations. In contrast to mediation effects, the moderator does not explain the relationship between the independent and dependent variable. Interaction effects, are characterized by a changing effect size or direction of an association between constructs by adding a moderating variable. The moderating variable consists of a multiplication of the independent variable and the moderator. In SEM, finding a significant effect between the moderating variable and the outcome variable, means the interaction effect occurs. (Hair et al., 2014)

The previously defined decision making characteristics were tested for moderation in Model 2 (see Table 5). Two insignificant effects were found. Risk Taking Propensity does not moderate the relationship between Perceived Control and Acceptance of Technology or Acceptance of Advice. Also two significant interaction effects were found. Sensitivity to Others' Opinion and moderates the relationship between Perceived Control, Acceptance of Technology and Acceptance of Advice. It has a significant negative effect (β = -0.129; p-value < 0.05). This means that it dampens the positive relationship between Perceived Control and

Acceptance of Technology. In the same manner Sensitivity to Others' Opinion weakens the relationship between Perceived Control and Acceptance of Advice (β = -0.142; p-value < 0.05). Figure 8 shows a visual representation of the interaction effects.

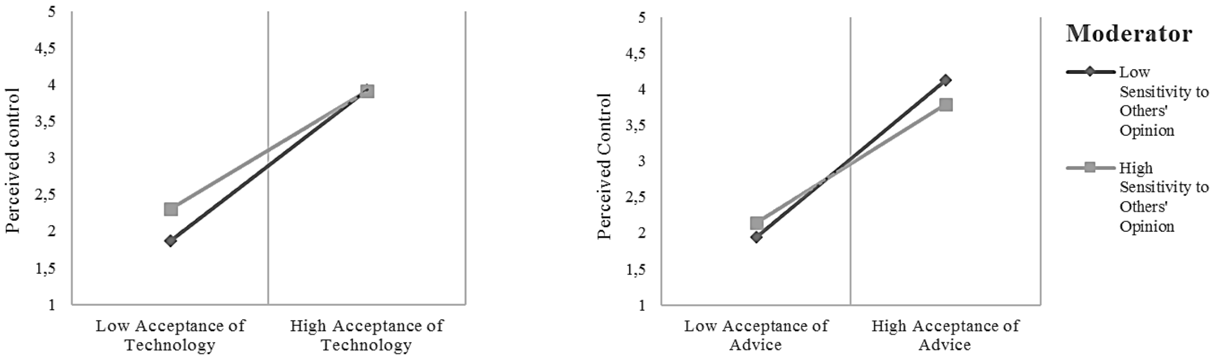


Figure 8: Interaction Effects of Sensitivity to Other's Opinion

4.5. Multi-Group Analysis

Multi-Group Analysis can be a good method to compare for a categorical variable in SEM. A Chi-square difference test was executed to check for significant differences per association of the model. For every association, the difference in chi-square and degrees of freedom is obtained from comparing the unconstrained model, with a model that separately constraints the regression weight of the associations (i.e. the constrained model). If the difference between the Chi-square and degrees of freedom is statistically significant, it means the constrained model does not fit equally well to the data as the unconstrained model. This means that a significant differences between the level of Human-Like Appearance for the path coefficients that were constrained, can be assumed (Oerlemans, 2016). For every association, the differences are calculated in Microsoft Excel with values from AMOS. Table 6 shows the combined findings. As can be seen some associations appear to be significantly moderated by the level of Human-Like Appearance and some are not.

Figure 9 visualizes the significant findings per association (abbreviations in Table 1). The higher the level of Human-Like Appearance, the stronger the relation between Perceived Personalization and Perceived Control. This shows that the medium Human-Like Appearance has the strongest effect on the relation to Acceptance of the Technology and Acceptance of the Advice. In contrast, a high level of Human-Like Appearance shows, more than others, to strengthen the relation of Perceived Personalization to Perceived Control and weaken the negative relation of Trust in Automation to Privacy Concern. In addition, the low level of Human-Like Appearance has the strongest negative effect, from Privacy Concern to Perceived Control, and the highest strengthening effect on the relation between Trust in Automation and Perceived Control.

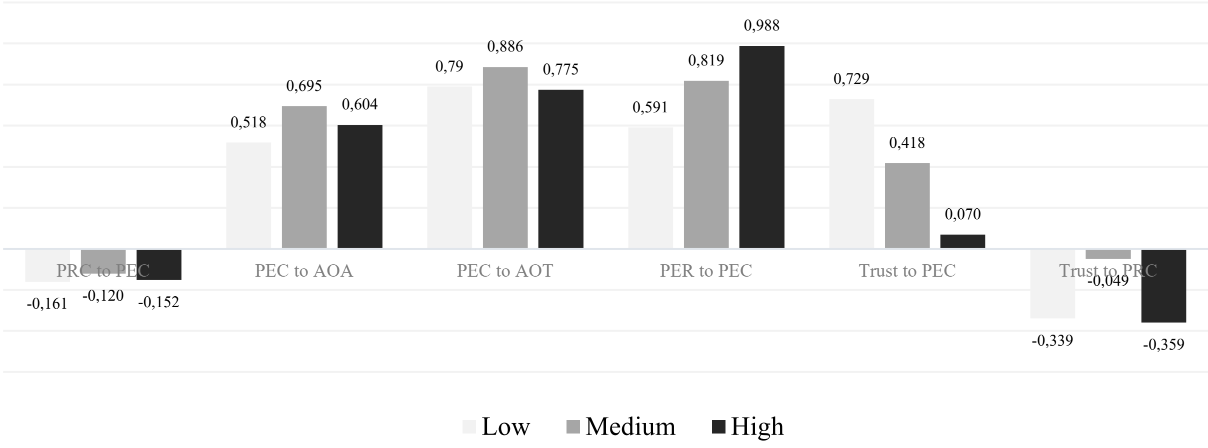


Figure 9: Moderating effect of levels of Human-Like Appearance

		Predictor		Dependent variable	Significance	Model 3 Low Human-Like β	S.E.	Medium Human-Like β	S.E.	High Human-Like β	S.E.
Main effects	*H1*	Perceived Personalization	→	Privacy Concern	Not Significant	-0,196**	0,14	-0,136**	0,14	-0,244**	0,14
	H2	Perceived Personalization	→	Perceived Control	*	**0,591***	0,12	**0,819***	0,12	**0,988***	0,12
		Perceived Personalization	→	Acceptance of Tech	*	**0,292****	0,16	**0,339****	0,16	**0,290****	0,16
	H3	Privacy Concern	→	Perceived Control	**	**-0,161****	0,05	**-0,120****	0,05	**-0,152****	0,05
	H4a	Perceived Control	→	Acceptance of Technology	Not Significant	0,790***	0,12	0,886***	0,12	0,775***	0,12
	H4b	Perceived Control	→	Acceptance of Advice	*	**0,518*****	0,18	**0,695*****	0,18	**0,604*****	0,18
Control		Age	→	Acceptance of Technology	Not Significant	0,224**	0,54	0,211**	0,54	0,229**	0,54
		Age	→	Acceptance of Advice	Not Significant	0,103*	0,62	0,126*	0,62	0,129*	0,62
		Age	→	Perceived Control	Not Significant	-0,080	0,50	-0,066	0,50	-0,830	0,50
Interaction		Risk Taking Propensity	→	Acceptance of Technology	Not Significant	0,022	0,60	0,037	0,60	0,020	0,60
		Risk Taking Propensity	→	Acceptance of Advice	Not Significant	0,082	0,70	0,097	0,70	0,192	0,70
		Sensitivity to Others' Opinion	→	Acceptance of Technology	Unidentified						
		Sensitivity to Others' Opinion	→	Acceptance of Advice	Not Significant	-0,068	0,17	-0,036	0,17	-0,032	0,17
		Experience	→	Privacy Concern	Not Significant	-0,064	0,63	-0,072	0,63	-0,081	0,63
		Experience	→	Perceived Control	Not Significant	0,342***	0,04	0,285***	0,04	0,352***	0,04
		Trust in Automation	→	Privacy Concern	***	**-0,339*****	0,09	**-0,049*****	0,09	**-0,359*****	0,09
		Trust in Automation	→	Perceived Control	***	**0,729*****	0,25	**0,418*****	0,25	**0,070*****	0,25

****Significant at P<0.001; ** Significant at P<0.05; *Significant at P<0.1.*

Table 6: Multi-Group Analysis on the level of Human-like Appearance

4.6. Decision Making Segments

Risk Taking Propensity (RTP) and Sensitivity to Others' Opinion (STO) together form the y-axis and x-axis of the Forrester Matrix of customer groups, based on decision making characteristics (Figure 4). The respondents were divided in Self-directed, Validator, Avoider and Delegator. First the existing variables were split at the median into groups of low and high characteristics (median = 2.5 for RTP; median = 3 for STO) and transformed into a new Forrester Segmentation variable in SPSS. Figure 10 shows the composition of the new dummy coded variable (1 = self-directed with n = 21; 2 = validators with n = 42, 3 = avoiders with n = 76, 4 = delegators with n = 50).

The four remaining groups were too small to conduct a reliable Multi-Group Analysis in SEM, therefore analysis of variance (ANOVA) was conducted in SPSS. The ANOVA tests to what extent the groups of the categorical variable are distinguishable for constructs of the structural model. Appendix 7.23 shows the findings being insignificant, meaning that the null-hypothesis of equal variance cannot be rejected. The variance among the four groups does not differ for the main factors of analysis.

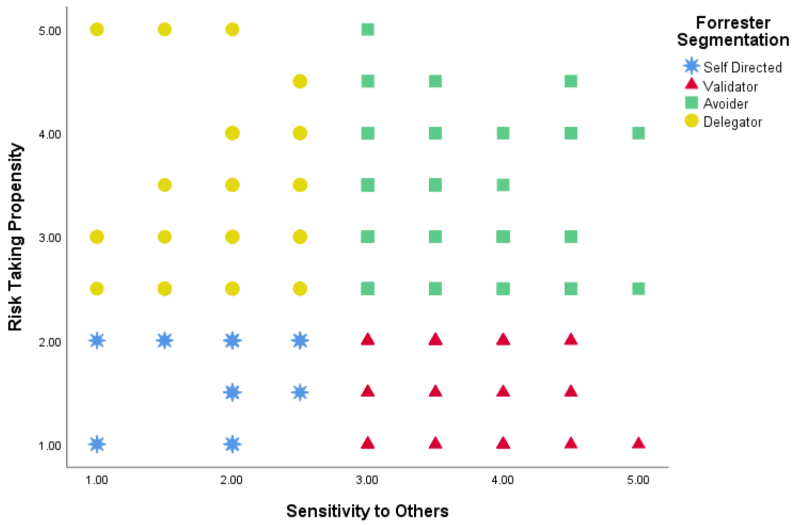


Figure 10: Customer Segmentation

5. Discussion and Conclusion

This research aims to reduce companies' uncertainty and risks that are associated with introducing a new service agent for customers in the context of financial products and insurances, by finding relevant customer perception mechanisms that influence acceptance of service agents. The main interest of this research was the Personalization-Privacy Paradox associated with customer acceptance. In order to find a more comprehensive understanding for customer acceptance, mediation effects of Perceived Control and interaction effects of different levels of Human Like appearance and decision making segments were also tested. As a result, this research provides empirical evidence and insight in relevant factors for customer's acceptance of the IRA and its advice. The following chapter will answer and discuss the previously established main question:

To what extent do the Personalization-Privacy Paradox, Perceived Control and the level of Human-Like Appearance affect customer acceptance of the IRA and its advice?

In brief, the findings show that customers are not as sensitive to Privacy Concerns in their experience with the IRA as was expected. In addition, perceived personalization and perception of control greatly impact customers' acceptance of the IRA and its advice. The results on different levels of Human-Like Appearance are rather ambiguous and the decision making segments did not moderate the findings. In the following chapter, the findings will be elaborated and related to the existing theory, answering the sub questions that were provided in Chapter 1.4 in sequence. Finally, implications for managers, limitations and further research suggestions are provided.

5.1. Theoretical Contributions

The first and most remarkable contribution of the research is the rejection of the Personalization-Privacy Paradox. This research finds that Perceived Personalization decreases the customer's Privacy Concerns. This means that for the IRA, niether the personal information that was requested nor the personal information that is recalled in the dialogue with the customer, is enhancing Privacy Concerns. The results contradict the findings of Smith et al. (2011) and Li & Unger (2012), who stated that Perceived Personalization has a significant negative effect on Privacy Concern, hence the Personalization-Privacy Paradox. However, the findings of this research are in line with Chen & Sundar (2018); when a customer initiates the request for the personalized advice, it does not induce Privacy Concerns. In that context customers can even be motivated to share personal information in return for a service that is perceived personalized. Xu et al. (2010) stated that a personalized service does not enhance Privacy Concerns with customers if overt personalization techniques are adopted. No clear guideline on the types can be given, as the IRA recalled also purchase history, which is a grey area for explicit or implicit personalization. Further investigation of the Personalization-Privacy Paradox in relation to the IRA is recommended for differentiating customer perception on overt and covert personalization within in financial advisory settings. The research findings complement the theory of Awad and Krishnan (2006) that the effect of the Personalization-Privacy Paradox can vary by context. To conclude, in the context of financial advisory setting, an IRA that is perceived personalized by the customer, does not induce Privacy Concern and its benefits can be seized.

Note that the effect of Perceived Personalization on Privacy Concern is small. The negative impact of Privacy Concern on Perceived Control is small as well. This contradicts the findings of Zeithaml et al. (2002) who indictate Privacy Concern is a key dimension of customer peception of e-services. Therefore, the Personalization-Privacy Paradox is less important than expected.

Second, noteworthy results are found in the analysis of Perceived Control. Placing Perceived Control as a mediator after the Personalization-Privacy Paradox and before the customer acceptance factors, two specific insights are found into its attribution to the literature. To begin with, respondents' Privacy Concern has a small negative impact on perception of control over the service encounter. This supports the research of Awad & Krishnan (2006), finding Privacy Concerns reducing a customers Perceived Control. What is more, the perception of a personalized service agent has a strong positive effect on Perceived Control. In line with Chen & Sundar (2018), Perceived Personalization is shown to be a strong predictor of Perceived Control. The representation of a customer's individual needs by the IRA increases the amount of control a customer feels over the service encounter. This can be supported by the IRA's task to give personal recommendations, and thus Perceived Personalization gives the customer an increased perception of control over the service encounter.

Moreover, the results show Perceived Control as an important predictor for customer acceptance of the IRA and its advice. This adds to the Theory of Planned Behavior (TPB), that Perceived Control is a predictor of customer attitude and behavior. In addition to the Theory of Planned Behavior there is a distinction between Acceptance of Technology and Acceptance of

Advice. The findings show that Perceived Control has a large effect on Acceptance of Technology, and a medium effect on Acceptance of Advice. It means that perception of control is slightly less effective in influencing customers to Accept the Advice given by the IRA, than to Accept the Technology of the IRA itself. Note that a direct relationship was shown between Perceived Personalization and Acceptance of Advice, but not between Perceived Personalization and Acceptance of Technology. Explanation for this difference can be found in the advice being established on a customer's individual situation (i.e. personalized), while the technology is not customized for a customer's personal situation.

Consequently, in this research the perception of control is arguably the most important predictor of customer acceptance in the context of the IRA. This not only means that especially in the rapidly developing SST context it is expected to remain an important point of attention predicting acceptance, but also that it is another benefit of enhancing personalized service. Over time, many researchers have validated the importance of Perceived Control for attitude and future behaviour (Ding, Jen-Hwa Hu, & Liu Sheng, 2011; Fernandes & Pedroso, 2017; Shi et al., 2016; Wang et al., 2011). This research shows it will remain an important factor in the era of IATs and continuously developing e-commerce.

Third, this research aimed to contribute insight into the association between customer acceptance and the level of Human-Like Appearance. Unfortunately, the results do not diverge to a specific preferable prototype of Human-Like Appearance. And do not provide support for the Uncanny Valley theory either, which states that there are negative effects when the appearance does not match the customer perception of the IRA (Mori et al., 2012). Moreover, insignificant results indicate indifference in the interaction effect of the level of Human-Like Appearance on the measured associations.

On the contrary, the research findings also show that the level of Human-Like Appearance sometimes moderates the found associations (see Figure 9). There is consensus in previous literature on the importance of appearance of service agents, and its significant association with customer perception of the IRA (Beer et al., 2011; Stein & Ohler, 2017). However, it is more common to have trouble finding guidelines for the influence of the level of Human-Like Appearance, for example in the research of Qiu & Benbasat (2009) and Wakefield et al. (2011). This is supported by the ambiguous effects of levels of Human-Like Appearance. For example, it is found that the positive relationship between Perceived Personalization and Perceived Control is mostly strengthened by a medium level of Human-Like Appearance. A medium level of Human-Like Appearance also weakens the negative relation between Privacy Concern and Perceived Control the most. In addition the medium level Human-Like Appearance of the IRA strengthens the relationship between Perceived Control and the Acceptance of Technology of the IRA. Trust in Automation enhances Perceived Control the most for lower Human-Like Appearance.

Unfortunately, from the set up of this research no further explanation can be given for the differences in findings in the levels of Human-Like Appearance. And the question remains whether the customers actually responded to the different levels of Human-Like Appearance. Rather than finding an explanation for the ambiguity of the results, it is recommended that the level of Human-Like Appearance should be tested in an actual interactive field experiment for more relevant and reliable results.

Fourth, the decision making segments are shown to have equal variance over the customer perception and acceptance factors and Perceived Control. This shows that for customer acceptance of the IRA and its advice there is no distinction in the customer decision making segments established in Chapter 2.7, the Self-directed, Validator, Avoider and Delegator. From previous literature, distinguishing for different decision making segments can be important, but that was not found in this research. Remarkably, the factor of Sensitivity to Other's Opinion separately moderates both the relationship of Perceived Control and Acceptance of Technology and the relationship of Perceived Control and Acceptance of Advice (see Figure 8). This means that with customers who are more sensitive to other's opinions, lower customer acceptance for the amount of Perceived Control is expected.

Finally, the Trust in Automation is shown to decrease Privacy Concerns and increase the perception of control over the service encounter. This is in line with the findings of de Ruyter et al. (2000). It shows that a customer's Trust in Automation positively affects the predictors of customer acceptance and should be involved as an important customer attitude, which attributes to the TPB in predicting customer intention and behavior in this context. Experience with chatbots did not have a significant effect on the customer perception of the IRA and, even though this result is counterintuitive, experience is thus considered less relevant in this context than Trust in Automation or Sensitivity to Other's Opinion.

5.2. Managerial implications

An Interactive Recommendation Agent (IRA or service agent) has great potential for both the company and its users. The challenge for achieving the benefits of a more interactive and personalized Self-Service Technology (SST) is gaining insight in the customers perception and acceptance to reduce risks and uncertainty associated with the introduction of a new service agent. This research found mechanisms relevant for customer acceptance of IRAs within the context of insurance products. Based on the results, three key managerial recommendations are derived from this research, so that the company can improve their strategy on customer acceptance of an IRA and its advice.

5.2.1 Personalization of the IRA

Enhancing personalization of the IRA has been shown to be an important stimulator for customer acceptance of the IRA and its advice. The results confirm that customers' Perceived Personalization increases customers' feeling of being in control, which has been shown to enhance customer acceptance of the service agent and its advice. Remarkably it is also found that when using the customer's personal information for personalization, there is no potential risk of inducing Privacy Concerns among customers. This outcome is consistent with earlier research on customer personalization, that the personalized context-sensitive content of the IRA is likely to enhance utility of the technology (Xiao & Benbasat, 2007). It is therefore highly recommended to personalize the IRA.

In practice, enhancing personalization means using personal information of the existing customer in the dialogue to optimize advice. An example can be found in the prototype of the IRA, in which a customer's personal information, as well a visual map detailing his address, income and family situation were recalled for the user to create a personalized advice (see Appendix 7.8). This recall of personal information has been proven not to raise the user's Privacy Concerns, in the situation that a customer takes the initiative to use the IRA for an advice based on their personal information. The company should be careful not to draw conclusions for all kinds of personalization. Implicit techniques (covert personalization), for example GPS tracking or browsing history, are not tested in this research and previous studies suggest they yield a different customer response. In conclusion, personalization should be enhanced in such a way that customers continue to feel in control of the service encounter, to not hinder the acceptance of the IRA.

5.2.2 Customers' perception of control

When customers feel in control of the service encounter, not only will the IRA be accepted more easily; its task fulfillment, the acceptance of advice, will be enhanced also. This is in accordance with previous studies that found a customer's Perceived Control over a service encounter was an excellent predictor of the customer's perception and attitude for SSTs (Collier & Sherrell, 2010; Demoulin & Souad, 2016; Wang et al., 2011).

To increase Perceived Control and thus customer acceptance of the IRA and advice, this research finds Perceived Personalization a strong predictor. In addition, the appearance of the IRA can also influence the perception of control among the customers, though to a lesser extent than other factors. The results show that of the three different levels of Human-Like Appearance that were tested, the prototype with a high Human-Like Appearance strengthened the effect of personalization on Perceived Control more than the other prototypes (see Chapter 4.5). Moreover, several implications from previous literature (see Chapter 2.4) are, clarity in information presentation, 24/7 service, increasing transparency about personal information processing and explicit personalization (Chen & Sundar, 2018; Rust & Kannan, 2003; Wolfinbarger & Gilly, 2001). Overall, customers perceive control over the service encounter, is found to be a strategic factor that substantial benefits customer acceptance of the IRA and its advice.

5.2.3 The level of Human-Like Appearance of the Service Agent

The insights associated with the appearance of the IRA were not as clear as as those associated with personalization and Perceived Control. On one hand, the current findings reveal a significant difference in the perception of customers per level of Human-Like Appearance (see Figure 9), meaning that the appearance of the IRA affects some of the associations from this study. On the other hand, not all associations are affected by the different designs of the IRA. Therefore, it is difficult to find guidelines in this area. Further investigation of the appearance of the IRA is recommended, with a larger respondents group, a real interactive setting. That way the actual relevance and returns that were found in theory (see Chapter 2.8) can be established with more reliability.

5.3. Limitations and future research

Apart from theoretical and managerial implications, this research found limitations that leave room for future research. Firstly, an important limitation lies in the design of this research. The experiment being conducted with a prototype video, and only the perception of the customer and not their actual behavior could be measured. In addition, the personal information shown to the respondents in the experiment was not their own, but from a standardized example situation. Within the context of personalization and Perceived Control as a researching factor, a field experiment might have been more accurate (Boeije et al., 2009). Due to time and development constraints this was not feasible, as the actual IRA was not available for use at the time of the research. It is recommended to do a follow up study specifically for measuring the factors of Privacy Concern and Human-Like Appearance in the future.

Secondly, respondents did not score the appearance of the IRA on the scale of human-likeness in the survey. Thus, the anticipated levels of Human-Like Appearance are merely theoretical and could not be tested against the practical perception of the respondents. In the future, an additional manipulation check is important to conduct in order to explain the results and improve the validity of the research.

Thirdly, the current sample was not fully representational of the company's customers. Even though age and educational background were comparable, gender was not. Using the method of SEM in AMOS, which was considered the most appropriate (see Chapter 3.6), it was not possible to adjust a weight to gender in the model.

Fourthly, the research does not claim to be generalizable to broader contexts. The respondent groups only consist of adult Dutch citizens that have home or vehicle insurance at Independer. Especially because different cultural factors may influence the perception of human-robot-interaction, these findings are not intended to be generalized in a broader national or international context (Trovato et al., 2013).

Finally, the theoretical model in this context of research should be seen exploratory. Even though the separate factors are highly interesting in the academic field, the combination of the Personalization-privacy Paradox with Technology Acceptance theories needs replication to gain more reliability of the results.

6. Resources

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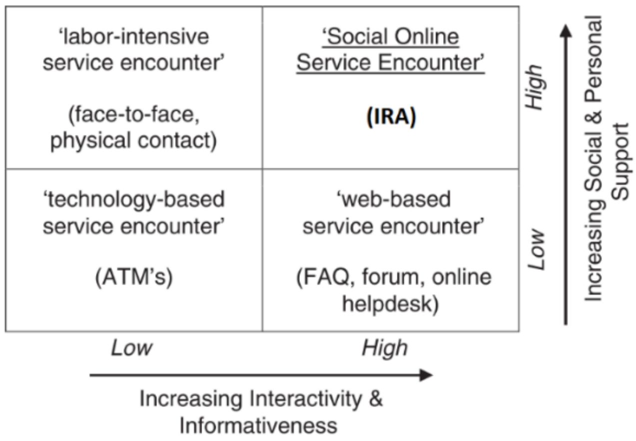
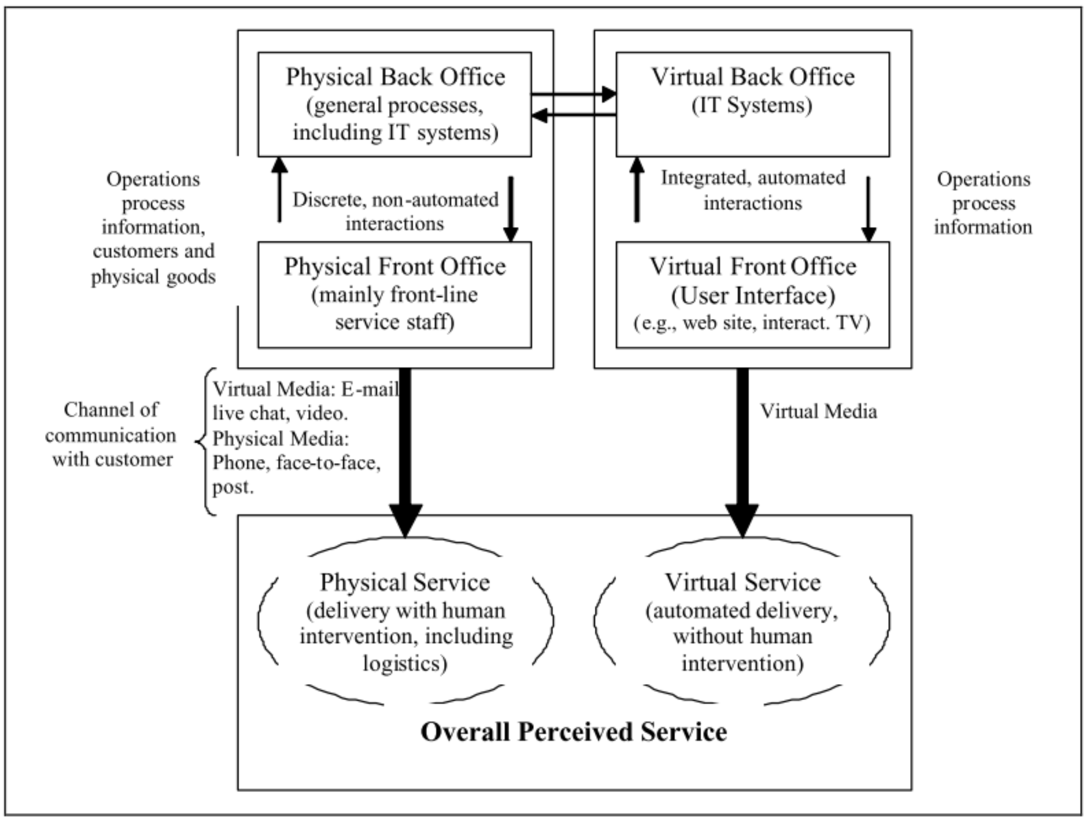
7. Appendices

7.1. Technology Infusion Matrix



(Retrieved from: Verhagen & Feldberg, 2014)

7.2. Framework for Multi-Channel Services



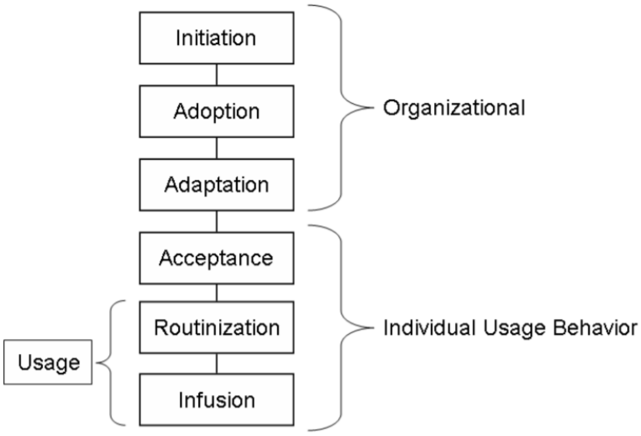
(Source: Sousa & Voss, 2004)

7.3. Marketing Taxonomy of AITs

Agent Characteristics	Marketing Objectives/Concepts: Market Governance	Customer Orientation	Competitor Orientation	Learning Orientation
Information Search & Acquisition	*Market Information Agents:* Public information of every agent e.g., GRAPPA	*Customer Intelligence Agents*: e.g., Prospect Miner, Customer profiling Webwatcher, NewsDude.	*Competitor Intelligence Agents*: e.g., Active Business.	*Learning Search Agents*: Price search, product search, merchant search e.g., Fido, Bargain-finder, Firefly.
Information Analysis: Pattern recognition, discovery, analytic problem solving, analogy	*Market Analysis Agents*: Market analysis, Matchmaking e.g., LARKS (Language for Advertisement and Requests for Knowledge Sharing)	*Customer Information Analysis Agents* : Buyer preference, acquisition, collaborative filtering, e.g., ADEPT, Letizia, Personal searcher.	*Competitor Analysis Agents*: e.g., memory-based reasoning in real time, e.g., Kora, NetBase, Deepblue.	*Learning Analysis Agents*: Product brokering, e.g., Addall
Interaction and Negotiation: proactive/reactive, rule-based, game theory–based, social welfare–based.	*Market Negotiation Agents*: Brokering Facilitator/ negotiation mechanisms, results of past negotiations e.g., Scottrade brokerage agent	*Customer Negotiation Agents:* Relating customer history, preferences, willingness, and ability to pay, e.g. Priceline automated agents	*Competitor Response Agents:* Understanding and proactively pre-empting or responding to competitor strategies and tactics in real time, e.g. Lending Tree, Deepblue.	*Learning Negotiation Agents:* Chanel relations and negotiations, Price negotiations, bidding strategies, e.g. Bazaar, Inspire, Smartsettle, Deepmind.
Autonomy/ Decision Making	*Market Authentication Agents:* availability Matchmaking e.g., LARKS	*Recommendation Agents:* Accelerated real time offers in milliseconds based on customer information e.g., Lycos, Pragmatic Chaos	*Competitive Decision Making Agents*: Real time price comparisons, and pricing tactics evaluation and response. e.g. pricewatch	*Learning Decision Agents:* Price setting, recommendation agents, customization, personalization, advertising. e.g. truecar
Collaborative (All characteristics of individual agents above plus)	*Multi-agent systems:* BDI systems. Trust mechanisms, public information of every agent. e.g. LIDS	*Coalition Agents:* formation for group buying and negotiations, Privacy, confidentiality, authentication, availability Systems. e.g. CATS, Jasmere	*Competitive Collaborative Agents*: Threats, masquerade, trust, BDI systems. e.g. LIDS, NED	*Learning Collaboration Agents:* Vickery auctions, English auctions Anonymity, traceability, traffic analysis, liability. e.g., Saffronart

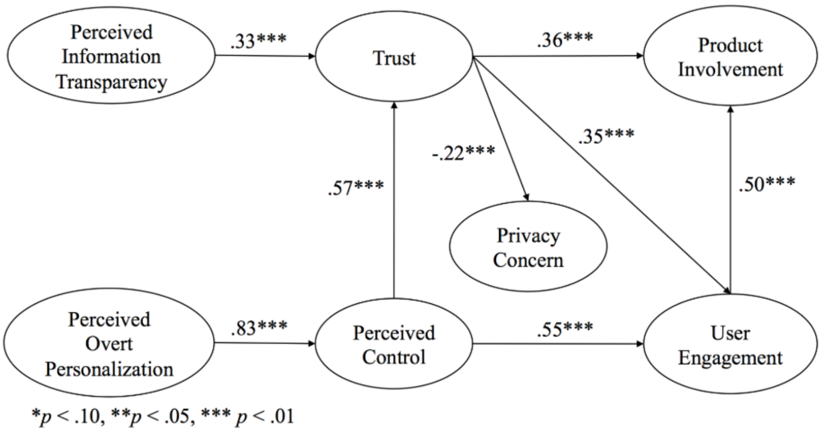
(source: Kumar et al., 2016)

7.4. IT Implementation Stages



(source: Kaldi, Aghaie & Khoshalhan, 2008)

7.5. Mediation of Perceived control



(source: Chen & Sundar, 2018)

7.6. Previously validated scales of Human-Like Appearance

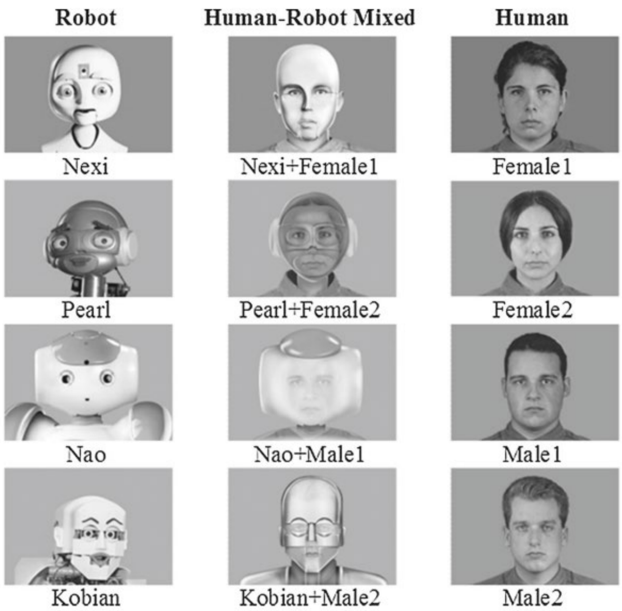


Fig. 2 Pictures used in the study to represent different levels of human-like appearance

(Source: Prakash and Rogers, 2015)

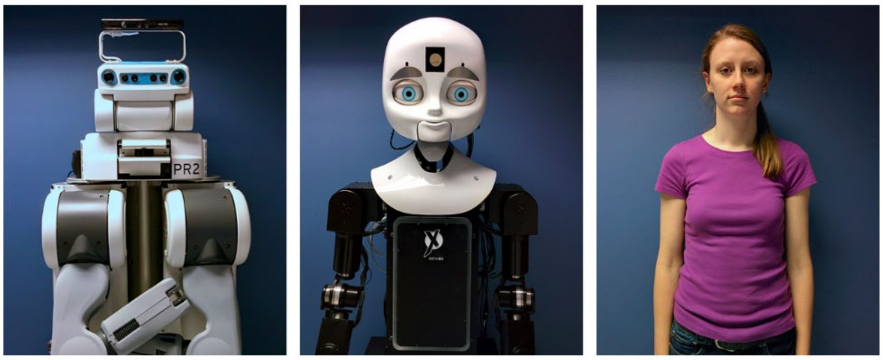
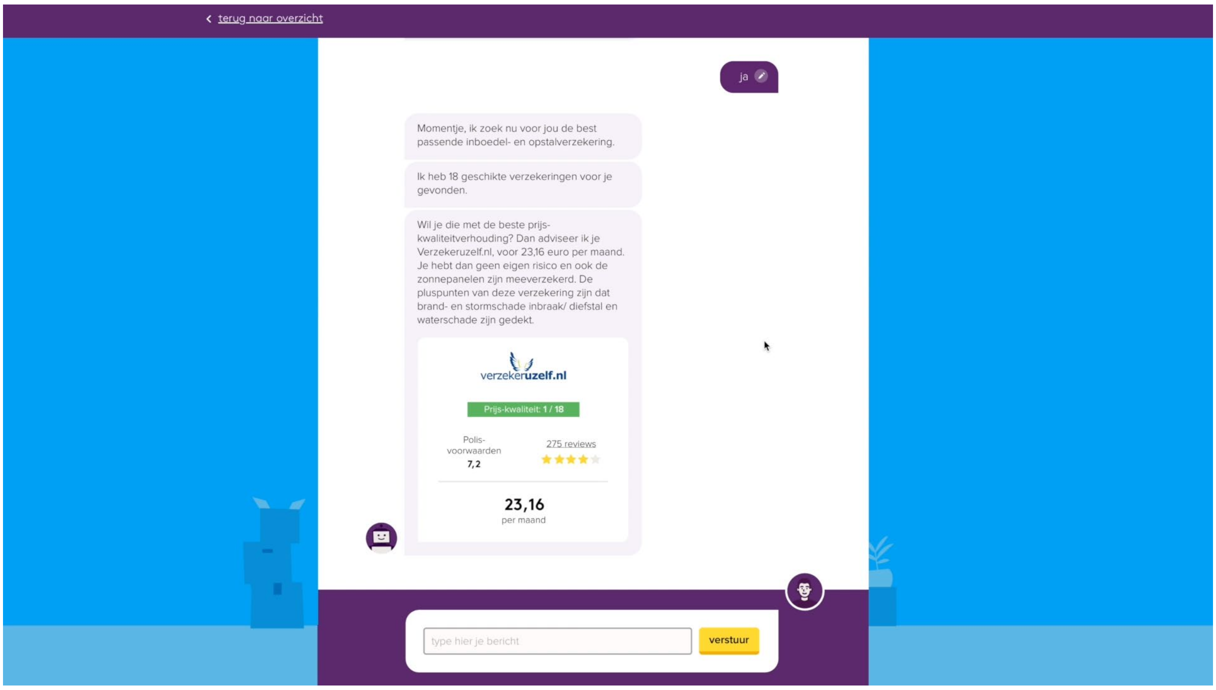


Figure 3. Exemplars of agent categories: robots with *low* and *moderate* human likeness (left and center, respectively), as well as a human (right).

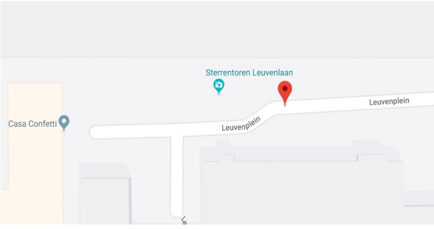
(source: Strait el al., 2015)

7.7. Prototype



7.8. Dialogue with IRA (in Dutch)

R		Hallo Joep, welkom terug bij Independer!
R		Ik ben Indy, een online assistent die jou advies kan geven over je woonverzekering.
R		Waar kan ik je mee helpen?
	K	ik heb een ander huis gekocht.
R		Gefeliciteerd Joep!
R		…
R		Je hebt nu bij ons een inboedel- en opstalverzekering voor 20 euro per maand. Het adres dat verzekerd is, is Wibautstraat 137 in Amsterdam. Wil je dit adres wijzigen?
	K	**(Ja)** (nee)
R		Oke, laten we beginnen.
R		Wat is de postcode en het huisnummer van je nieuwe woning? (bijvoorbeeld 1234AB 10)
	K	**3584LJ 176**
R		…

R		 Gaat het om Leuvenplein 176 in Utrecht?
	K	**(ja)** (nee)
R		Ook voor je nieuwe woning adviseer ik je om een inboedel- en opstalverzekering af te sluiten. Wil je dit?
	k	Wat is ook alweer een opstalverzekering?
R		Met een opstalverzekering is je woning goed verzekerd voor onder andere brand-, storm- en waterschade, inbraak en diefstal. Ook je keuken, badkamer en houten vloer zijn meeverzekerd.
R		Wil je een inboedel- en opstalverzekering afsluiten? Of alleen één van beide?
	K	(Inboedel) (Opstal) **(Inboedel + Opstal)** (Meer informatie)
R		Om je goed te kunnen adviseren heb ik nog wat vragen over je nieuwe woning.
R		Waar zijn de buitenmuren van je nieuwe huis van gemaakt?
	K	**(bakstenen of beton)** (hout)
R		Waaruit bestaat (het grootste deel) van het dak?
	K	(dakpannen) **(plat dak)** (leisteen) (kunsttof riet) (riet)
R		Heb je ook zonnepanelen op de woning?
	K	**(ja)** (nee)
R		Goed om te weten, want vaak zijn deze niet automatisch meeverzekerd. In ons advies houden we hier rekening mee.
R		Eerder heb je aan ons doorgegeven dat je samenwoont met je partner en je kind. Klopt dat nog steeds?
	K	**(ja)** (nee)
R		En ligt je inkomen nog steeds tussen 2.001-3.000 euro netto per maand?
	K	**(ja)** (nee)
R		Momentje, ik zoek nu voor jou de best passende inboedel- en opstalverzekering.
R		Ik heb 18 geschikte verzekeringen voor je gevonden.
R		Wil je die met de beste prijs-kwaliteitverhouding? Dan adviseer ik je Verzekeruzelf.nl, voor 23,16 euro per maand. Je hebt dan geen eigen risico en ook de zonnepanelen zijn meeverzekerd. De pluspunten van deze verzekering zijn dat brand- en stormschade inbraak/ diefstal en waterschade zijn gedekt.

R		Wat vind je ervan?
	K	Zijn er ook andere opties?
R		A.S.R. biedt een alternatief voor 25,09 euro per maand, met precies dezelfde dekking als die van Verzekeruzelf.nl.
R		Een andere optie is Klaverblad. Als je deze bij Independer afsluit, betaal je 24,96 euro, in plaats van 26,61 euro. De dekking is precies hetzelfde als de andere verzekeringen. Maar er is 225 euro eigen risico bij schade door inbraak als je in Amsterdam, Rotterdam, Utrecht of Den Haag woont. Dit geldt dus ook voor jou.
R		Is er een verzekering die je bevalt?
	K	Ja, de verzekeruzelf.nl lijkt mij de beste optie
R		Goede keuze Joep! Zal ik die voor je aanvragen?
	K	**(ja)** (nee) (weet ik niet)
R		Je hebt gekozen voor de Verzekeruzelf.nl, voor 16,16 euro per maand. Je kunt binnen 14 dagen kosteloos annuleren of een andere verzekering kiezen. Wanneer moet de verzekering ingaan?
	K	**01.09.2018**
R		Heb je nog steeds dezelfde Rabobank-rekening, die eindigt op 007?
	K	**(ja)** (nee) (weet ik niet)
R		Kunnen we de premie automatisch incasseren van die rekening?
	K	**(ja)** (nee) (weet ik niet)
R		Dank je wel. Ik vraag de verzekering nu direct voor je aan. Als de aanvraag wordt goedgekeurd, krijg je vandaag nog een digitale polis.
R		Heb je verder nog vragen?
	K	(ja) **(nee)** (weet ik niet)
R		Dan wens ik je veel plezier met je nieuwe woning, graag tot ziens!

7.9. Pre-test correlation matrix

	EXP	AOT	AOA	PEC	PER	TIA	PRCM	RTP	STO	Age
EXP	1									
AOT	0,189	1								
AOA	0,419	**.779****	1							
PEC	0,419	0,971	**1.00****	1						
PER	-0,419	**.538****	**.473****	**-1.00****	1					
TIA	0,099	**.401***	**.372***	0,945	**.505****	1				
PRC	-0,189	0,039	-0,173	-0,971	-0,246	0,111	1			
RTP	-0,204	0,149	0,207	0,803	**.378***	**.438****	-0,174	1		
STO	0,555	-0,134	0,082	0,988	0,043	-0,093	**-.432****	0,246	1	
Age	-0,419	-0,172	-0,265	**-1.00****	-0,095	-0,134	0,265	0,035	-0,325	1

7.10. Invitation e-mail 1

independer

> online versie

> woonverzekering > autoverzekering > reisverzekering > vergelijk energie

bij independer zijn we benieuwd naar uw mening

Beste mevrouw Bolk,

Wilt u als een van de eersten de mogelijkheden van onze online assistent zien? Dat kan! Want wij zoeken klanten die hier hun mening over willen geven. Heeft u 5-10 minuten om hierover een aantal vragen te beantwoorden?

ja, ik help graag even

Dit onderzoek doen wij samen met de Technische Universiteit van Eindhoven. Natuurlijk worden uw antwoorden vertrouwelijk behandeld en volledig anoniem gebruikt. Alvast hartelijk dank voor uw tijd!

Vriendelijke groet,

Ingeborg Koppenol
Independer

Wat vindt u van de e-mail?

goed | niet goed

over ons

> over Independer
> transparantie en onafhankelijkheid
> medewerkers
> vacatures

hulp en advies

035 - 626 55 44
> klantenservice
Stel ook je vraag aan ons via:

U ontvangt deze e-mail omdat u bij Independer uw verzekering heeft afgesloten. Als u dit soort e-mails niet meer wilt ontvangen kunt u zich hier uitschrijven.

Lees meer over het e-mailbeleid van Independer.

Independer N.V., Celebeslaan 2, 1217 GV Hilversum. KvKnr 34117387. AFM-verg.nr. 12012777 | © Independer 1999- 2018

7.11. Invitation e-mail 2

independer

> woonverzekering > autoverzekering > reisverzekering

> vergelijk energie

Beste mevrouw Bolk,

Bent u tussen de 18 en 54 jaar? Dan kunnen we uw hulp goed gebruiken. Heeft u weleens gehoord van een online assistent? We willen u graag betrekken bij de ontwikkeling van onze gloednieuwe service.

Onder alle deelnemers die de vragenlijst volledig invullen, verloten we 25 bol.com cadeaubonnen van tien euro. Het duurt in totaal 5-7 minuten om deel te nemen. U kunt tot uiterlijk **zondag 30 september** de vragenlijst invullen.

ja, ik help graag even

Alvast hartelijk dank voor uw tijd! Met uw hulp kunnen we onze dienstverlening blijven verbeteren.

Wij doen dit onderzoek in samenwerking met de Technische Universiteit van Eindhoven. Natuurlijk behandelen we de resultaten strikt vertrouwelijk en volledig anoniem. Ook worden uw antwoorden voor geen andere doeleinden dan dit onderzoek gebruikt. Heeft u nog vragen over het onderzoek, neem dan gerust contact met mij op via ikoppenol@independer.nl.

Alvast hartelijk dank voor uw medewerking,

Vriendelijke groet,

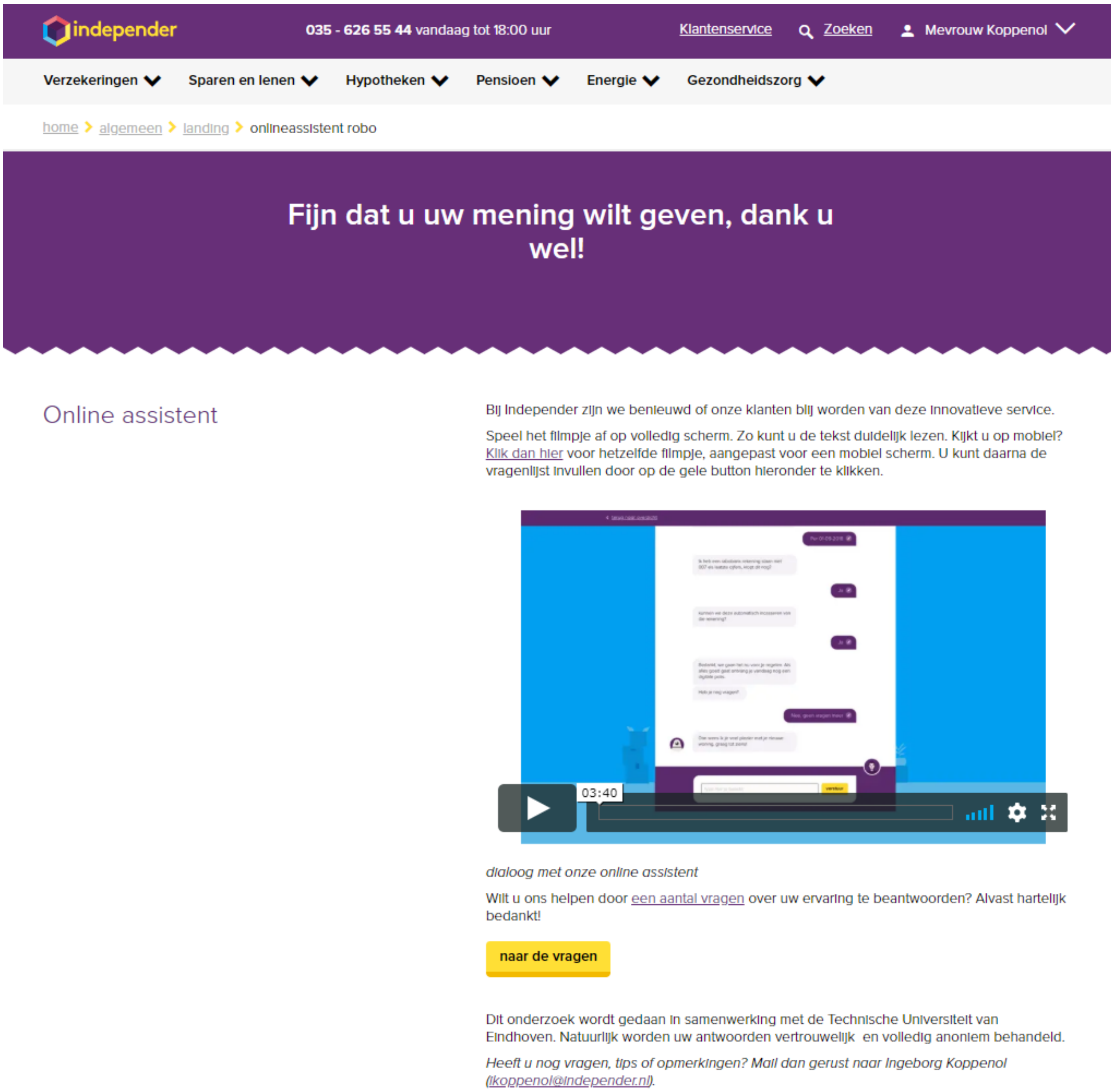
Ingeborg Koppenol
Independer

Lees hier de bijbehorende actievoorwaarden.

Wat vindt u van de e-mail?

7.12. Independer web page

	Link in mail to research web page
E-mail group 1	https://www.independer.nl/algemeen/info/landing/onlineassistent-robo
E-mail group 2	https://www.independer.nl/algemeen/info/landing/onlineassistent-rohu
E-mail group 3	https://www.independer.nl/algemeen/info/landing/onlineassistent-human



7.13. Promotional Conditions (in Dutch)

Actievoorwaarden "Winactie vragenlijst online assistent"

Independer wil graag dat je de vragenlijst over een online assistent helemaal invult. Als je dat doet, maak je kans op een Bol.com cadeaubon van 10 euro (de "Actie"). Dit is een eenmalige winactie waarop de Gedragscode Promotionele Kansspelen van 1 januari 2014 van toepassing is en waarop deze voorwaarden (de "Actievoorwaarden") van toepassing zijn.

1. Deelname

1.1. Je bent deelnemer en maakt kans op de Bol.com bon als je klant bent van Independer, als je persoonlijk per mail een verzoek van ons hebt ontvangen om de vragenlijst in te vullen, de vragenlijst voor 30 september volledig hebt ingevuld en je mailadres hebt achtergelaten in het daarvoor bestemde veld. Dit hoeft niet hetzelfde e-mailadres te zijn als waarmee je klant van ons bent geworden of waarop je bent uitgenodigd.

1.2. De Actie worden uitgeschreven door Independer NV gevestigd te Hilversum. Door deel te nemen aan deze winactie "maak kans op een bol.com bon als je deelneemt aan ons onderzoek naar een online assistent" ga je akkoord met deze Actievoorwaarden.

1.3. Deelname aan de Actie is strikt persoonlijk en niet overdraagbaar.

1.4. De vijfentwintig winnende deelnemers worden willekeurig gekozen door middel van een eenmalige trekking onder alle deelnemers. Winnaars worden via het daarvoor in de vragenlijst achtergelaten emailadres geïnformeerd. Over de uitslag kan niet geworden gecorrespondeerd.

1.5. Trekking vindt plaats op 30 oktober, winnende deelnemers ontvangen eenmalig een bol.com tegoedbon van € 10,-. De bon wordt digital opgestuurd via het daarvoor in de vragenlijst achtergelaten emailadres. Als het bericht niet kan worden bezorgd, vervalt het recht op de prijs en wordt een nieuwe winnaar getrokken.

1.6. Deelname door minderjarigen is niet toegestaan.

2. Persoonsgegevens

2.1. De vragenlijst is onderdeel van een onderzoek naar de bereidheid een online assistent te gebruiken. Dat doen we in samenwerking met Technische Universiteit van Eindhoven. De antwoorden op de vragenlijst worden anoniem verwerkt en strikt vertrouwelijk behandeld.

2.2. Je e-mailadres wordt uitsluitend gebruikt om kans te maken op de prijs en je te informeren als je gewonnen hebt. Als de vijfentwintig winnende deelnemers met succes zijn geïnformeerd, worden de e-mailadressen binnen één maand verwijderd.

3. Overige

3.1. Op deze Actie is het Nederlands recht en de gedragscode van toepassing. Dit kansspel is vrijgesteld van kansspelbelasting omdat de prijs minder is dan € 449,- (meer informatie).

3.2. Independer man deze Actievoorwaarden altijd eenzijdig wijzigen.

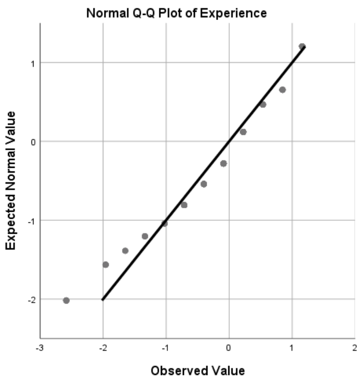
3.3. Het onderzoek is een initiatief van Independer. Er kan geen beroep gedaan worden op andere partijen, zoals Bol.com of de Technische Universiteit Eindhoven.

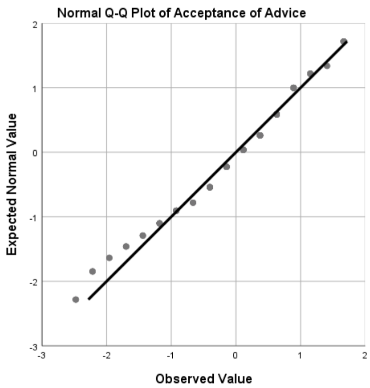
3.4. Opmerkingen, suggesties of klachten over deze Actie kunnen gemeld worden bij de klantenservice van Independer via 035 626 5544 of via de mail naar ikoppenol@independer.nl. Independer zal klachten zo snel mogelijk afhandelen.

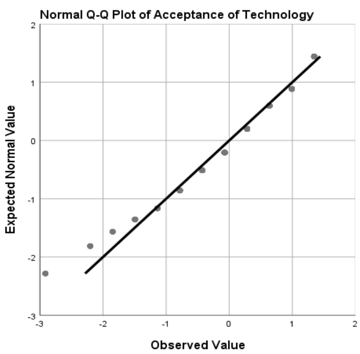
7.14. Variance between Sample Groups

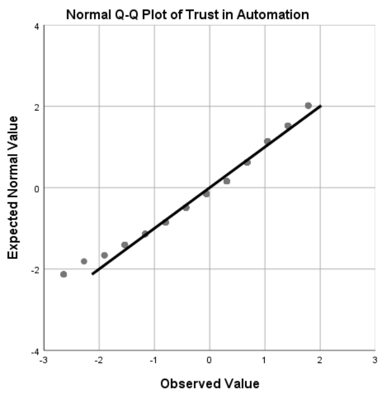
ANOVA						
		Sum of Squares	df	Mean Square	F	Sig.
age	Between Groups	14304,074	1	14304,074	102,295	,000
	Within Groups	26987,444	193	139,831		
	Total	41291,518	194			
gender	Between Groups	1,102	1	1,102	4,506	,035
	Within Groups	47,186	193	,244		
	Total	48,287	194			
education	Between Groups	5,776	1	5,776	5,070	,025
	Within Groups	219,896	193	1,139		
	Total	225,672	194			

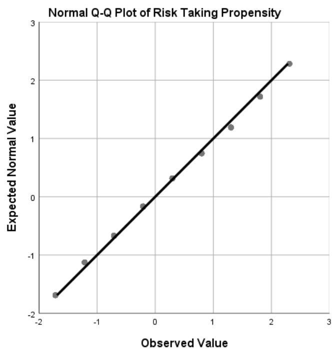
7.15. QQ Plots

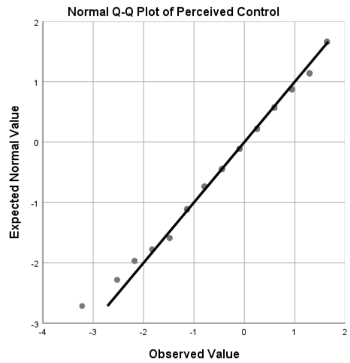


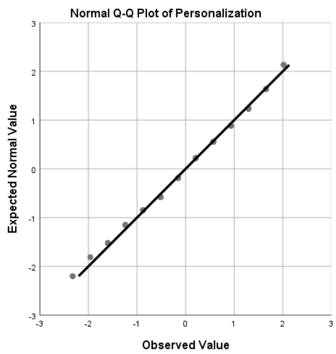


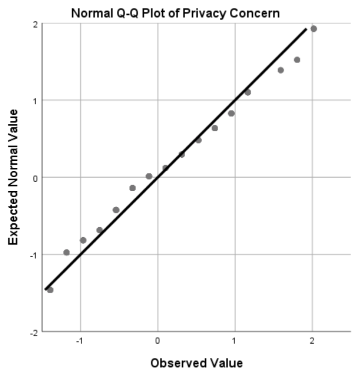


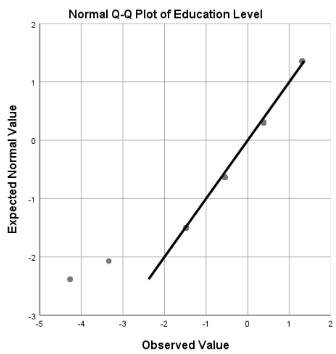


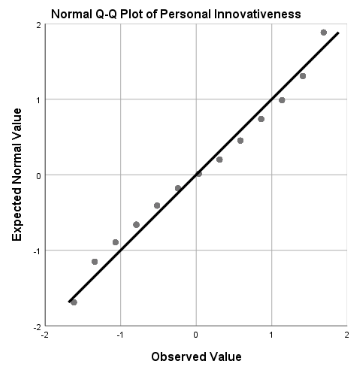

Normal Q-Q Plot of Risk Taking Propensity
Expected Normal Value
Observed Value

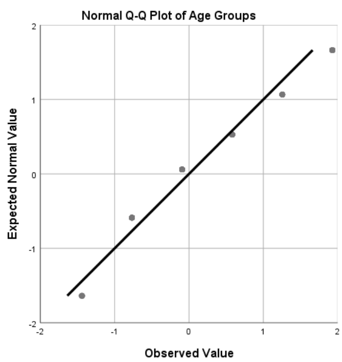

Normal Q-Q Plot of Perceived Control
Expected Normal Value
Observed Value

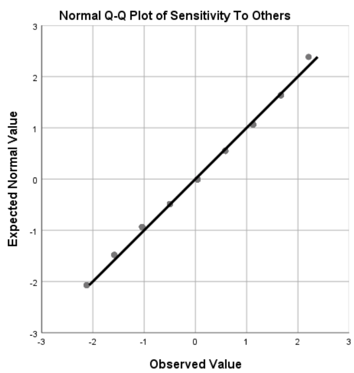

Normal Q-Q Plot of Personalization
Expected Normal Value
Observed Value


Normal Q-Q Plot of Privacy Concern
Expected Normal Value
Observed Value

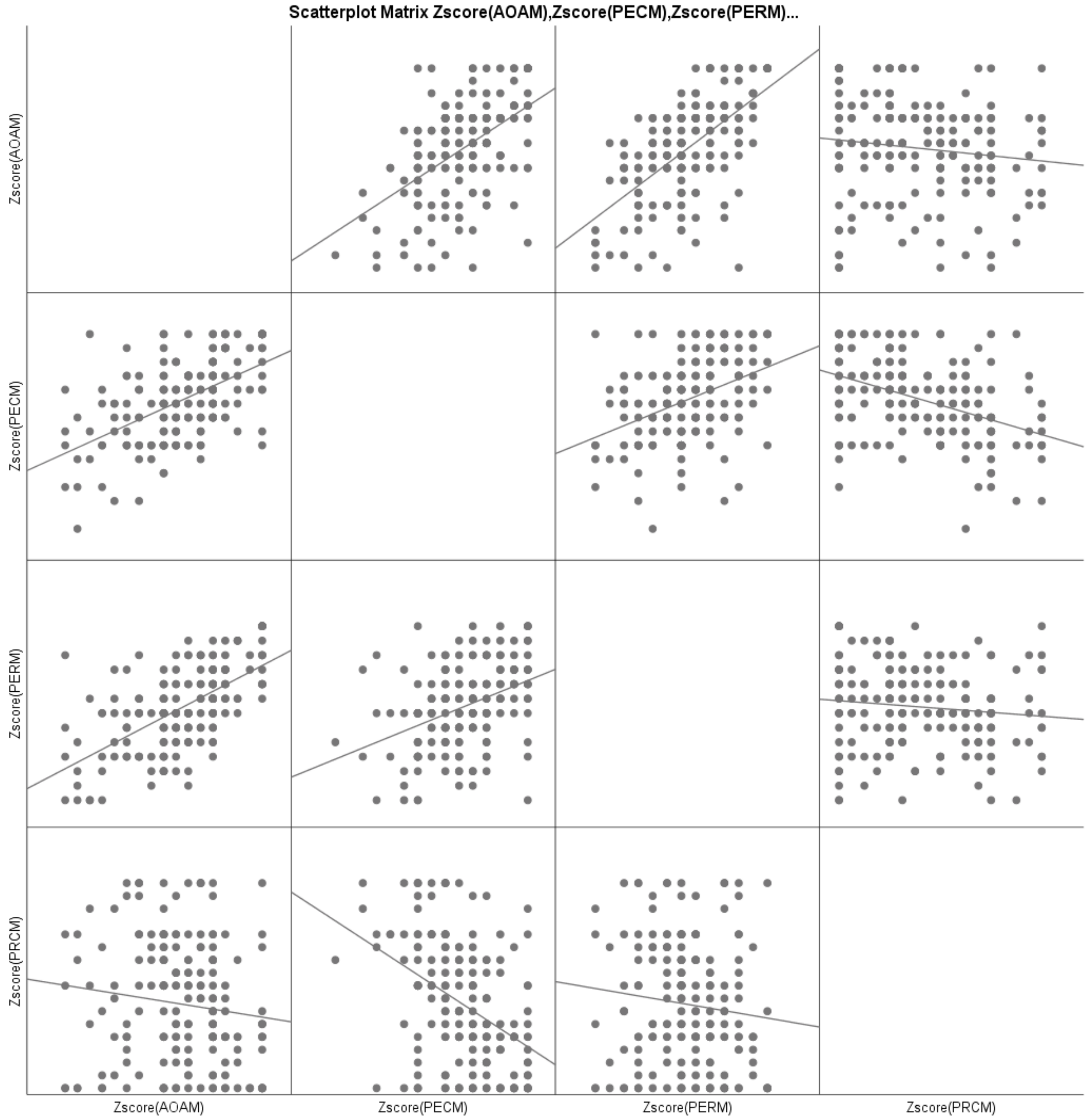

Normal Q-Q Plot of Education Level
Expected Normal Value
Observed Value


Normal Q-Q Plot of Personal Innovativeness
Expected Normal Value
Observed Value


Normal Q-Q Plot of Age Groups
Expected Normal Value
Observed Value


Normal Q-Q Plot of Sensitivity To Others
Expected Normal Value
Observed Value

7.16. Scatterplots



7.17. Multi-Collinearity

VIF Coefficients			
		Collinearity Statistics	
		Tolerance	VIF
	Zscore(EXPM)	.670	1.493
	Zscore(AOAM)	.396	2.524
	Zscore(PECM)	.441	2.268
	Zscore(PERM)	.506	1.975
	Zscore(TIAM)	.631	1.585
	Zscore(PRCM)	.739	1.354
	Zscore(RTPM)	.582	1.717
	Zscore(PEIM)	.567	1.762
	Zscore(STOM)	.886	1.129
	Zscore(YASM)	.768	1.303
	Zscore(XASM)	.693	1.442
	Zscore(Age_groups) Leeftijdgroepen	.839	1.192
	Zscore(Geslacht)	.883	1.132
	Zscore(Opleidingsniveau)	.832	1.202

7.18. One way Anova

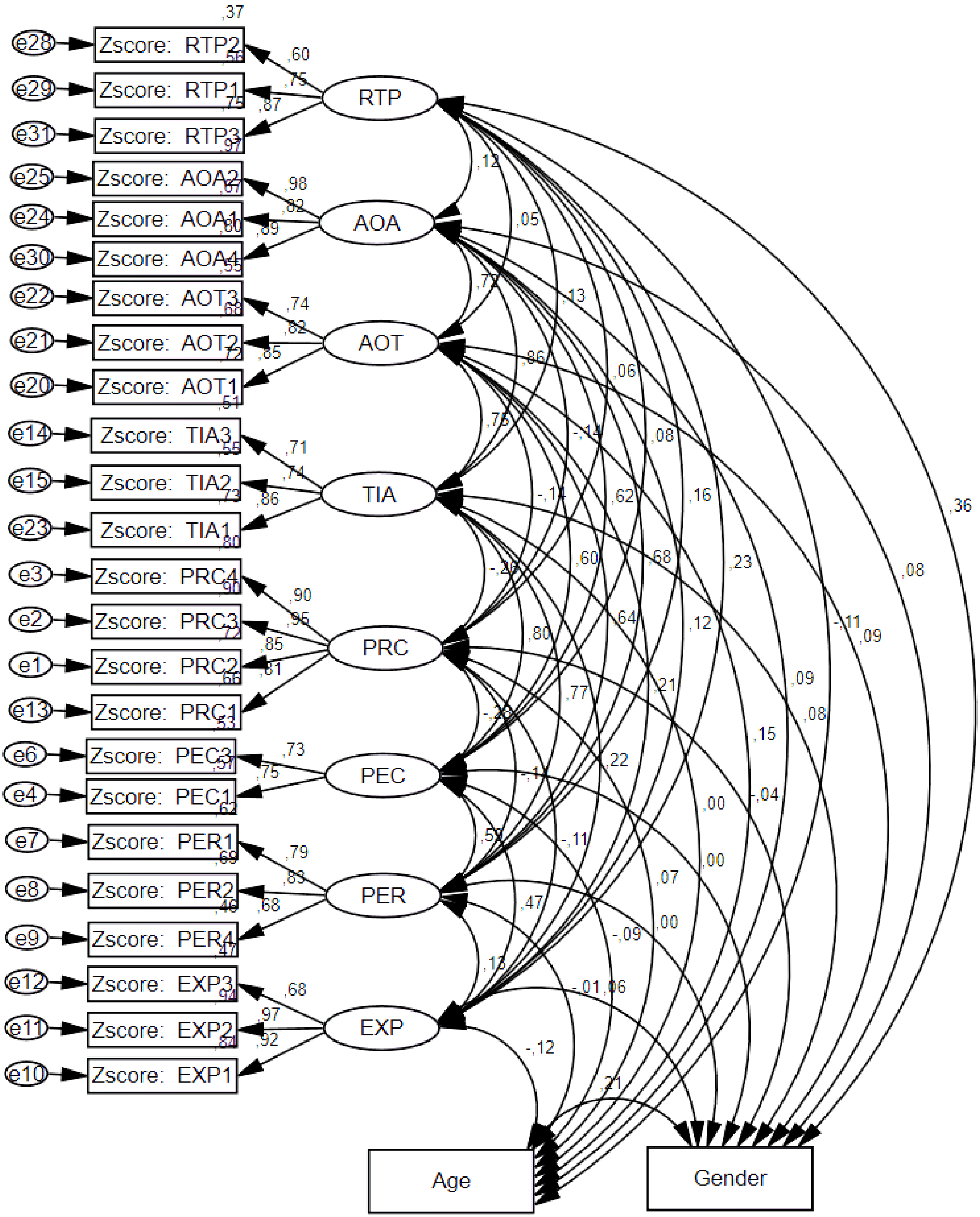
Anova						
		Sum of Squares	df	Mean Square	F	Sig.
Opleidingsniveau	Between Groups	2.384	2	1.192	1.122	**.328**
	Within Groups	190.188	179	1.063		
	Total	192.571	181			
Leeftijdgroepen	Between Groups	3.142	2	1.571	.705	**.495**
	Within Groups	396.405	178	2.227		
	Total	399.547	180			
Geslacht	Between Groups	.441	2	.220	.894	**.411**
	Within Groups	44.131	179	.247		
	Total	44.571	181			

7.19. Exploratory Factor Analysis

Pattern Matrix[a]										
	Factor									
	1	2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Zscore(AOA3)		0.367							**0.444**	
Zscore(AOA1)		0.623					0.347			
Zscore(AOA2)		0.829								
Zscore(AOA4)		0.787								
Zscore(AOT1)							0.770			
Zscore(AOT2)							0.631			
Zscore(AOT3)							0.783			
Zscore(PER1)					-0.442		0.342			
Zscore(PER2)					-0.883					
Zscore(PER3)										
Zscore(PER4)					-0.564					
Zscore(PEC1)									0.580	
Zscore(PEC2)										0.368
Zscore(PEC3)									0.464	
Zscore(PEC4)			0.300							0.347
Zscore(PRC1)			0.795							
Zscore(PRC2)			0.840							
Zscore(PRC3)			0.993							
Zscore(PRC4)			0.927							
Zscore(EXP3)	0.611									
Zscore(EXP2)	1.012									
Zscore(EXP1)	0.905									
Zscore(EXP4)										0.482
Zscore(TIA1)									0.580	
Zscore(TIA2)								0.305	0.487	
Zscore(TIA3)		0.330							0.364	
Zscore(RTP1)								0.790		
Zscore(RTP2)								0.486		
Zscore(RTP3)								0.723		
Zscore(PEI1)				0.762						
Zscore(PEI2)				0.816						
Zscore(PEI3)				0.832						
Zscore(STO1)						0.657				
Zscore(STO2)						-0.762				
Zscore(STO3)										0.495

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.
a. Rotation converged in 13 iterations.

7.20. Measurement model

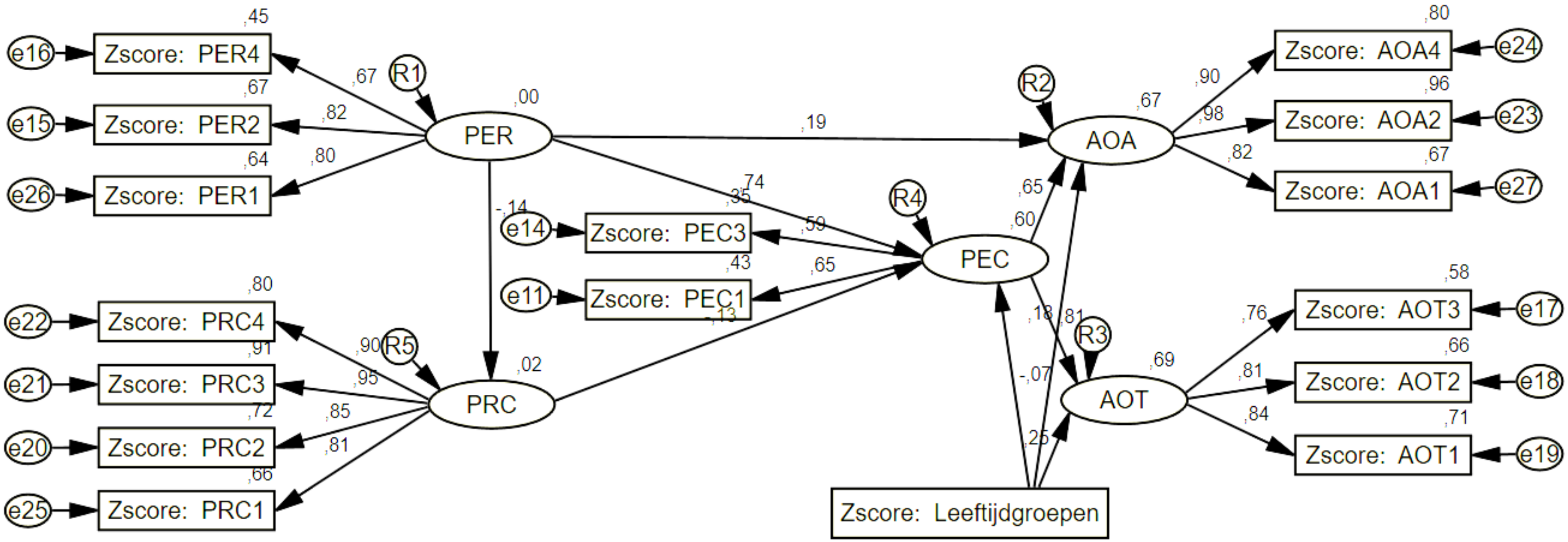


p-value=,000, cmin=457,240, df=256, cfi=,936, gfi=,851, rmsea=,065, nfi=,867, ifi=,937,

7.21. Control Variables

Predictor	Dependent Variable		Beta	S.E.
ZOpleidingsniveau	-->	PerceivedControl	0.113	0.056
ZAge_groups	-->	PerceivedControl	-0.058	0.056
ZGeslacht	-->	PerceivedControl	-0.004	0.056
ZGeslacht	-->	TechAcceptance	0.034	0.056
ZGeslacht	-->	AdviceAcceptance	0.039	0.057
ZAge_groups	-->	TechAcceptance	**0.248*** **	0.058
ZAge_groups	-->	AdviceAcceptance	**0.161****	0.058
ZOpleidingsniveau	-->	TechAcceptance	0.052	0.056
ZOpleidingsniveau	-->	AdviceAcceptance	-0.032	0.059
****Significant at P<0.001; ** Significant at P<0.05; *Significant at P<0.1.*				

7.22. Structural Model direct paths



p-value=,000, cmin=227,380, df=96, cfi=,934, gfi=,876, rmsea=,085, nfi=,892, ifi=,935,

7.23. Forrester Segmentation ANOVA

ANOVA						
		Sum of Squares	df	Mean Square	F	Sig.
Acceptance of Advice	Between Groups	3.303	3	1.101	1.103	.349
	Within Groups	184.697	185	.998		
	Total	188.000	188			
Acceptance of Technology	Between Groups	2.019	3	.673	.670	.572
	Within Groups	185.981	185	1.005		
	Total	188.000	188			
Perceived Control	Between Groups	.182	3	.061	.060	.981
	Within Groups	187.818	185	1.015		
	Total	188.000	188			
Personalization	Between Groups	2.630	3	.877	.875	.455
	Within Groups	185.370	185	1.002		
	Total	188.000	188			
Privacy Concern	Between Groups	.730	3	.243	.240	.868
	Within Groups	187.270	185	1.012		
	Total	188.000	188			
Age Groups	Between Groups	.331	3	.110	.109	.955
	Within Groups	187.669	185	1.014		
	Total	188.000	188			
***Significant at P<0.001; ** Significant at P<0.05; *Significant at P<0.1.						

7.24. Thesis Planning

Week			Acties	Fase
29	16-jul	22-jul	Mock-Up Dialoog Af	*Mock up & pre-test*
30	23-jul	29-jul	3 Versies En Filmpje Maken In Overleg Met Marcel	
31	30-jul	5-aug	Constructen En Items Finalizeren	
32	6-aug	12-aug	Online Enquete Af + Pretesten	
33	13-aug	19-aug	Data Analyse Methoden Uitzoeken	
34	20-aug	26-aug	Data Analyse + Pretest	
35	27-aug	2-sep	*Op Vakantie*	*wachten op data*
36	3-sep	9-sep	*Op Vakantie*	
37	10-sep	16-sep	Klanten Mailen	
38	17-sep	23-sep	Klanten Mailen 2	*Data analyse en resultaten*
39	24-sep	30-sep	Start Data Analyse	
40	1-okt	7-okt	Resultaten Schrijven	
41	8-okt	14-okt	H4 Af	
42	15-okt	21-okt	Feedback Verwerken	*Discussie en Conclusie*
43	22-okt	28-okt	Feedback Verwerken	
44	29-okt	4-nov	Discussie	
45	5-nov	11-nov	Discussie + Opsturen	*Finalizeren*
46	12-nov	18-nov	Conclusie + Summary	
47	19-nov	25-nov	Eindversie Inleveren	*Deadline*
48	26-nov	2-dec	Groenlicht Sessie	
49	3-dec	9-dec	5 December 14:00 Verdediging	
50	10-dec	16-dec		
51	17-dec	23-dec		