To share or not to share: A quantitative analysis on the effect of personality dimensions and the self-determination theory on the willingness to disclose private data

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Abstract

In recent years, digitalization has become an artificer of data that is being generated by society at an extraordinary pace. As technological shifts are determining the course of businesses in today's digital age, it is becoming increasingly important to understand the notions of big data. Ultimately, businesses that adapt to utilizing this data are the ones to hold a competitive edge. Therefore, it is becoming more vital to not only understand how this data can be used, but also how it is obtained. Personalized marketing, an approach powered by private data, has repeatedly shown its effectiveness. Recent evolvements in marketing have discovered a more niche marketing strategy, namely personality marketing, in which psychometrics are used to accurately target niche groups of people. This empirical study aims to gain insight into the complex notion of sharing private data by studying the influence of one's personality traits and motivators from the self-determination theory on behavioral intent, and contributes to an academic discussion that offers insight into the theoretical and practical implications of this new concept. A quantitative online experiment with 253 Dutch participants was conducted to explore the behavioral intent of sharing private data in the market of health insurance. Three experimental conditions investigated whether different motivators, specifically extrinsic or intrinsic, would moderate the relationship of someone's personality traits to behavioral intent. Contrary to prior research, findings demonstrate that personality traits are not a significant predictor of the willingness to disclose private data, nor when different motivators derived from the self-determination theory moderated this relationship. However, a significant multiple regression model showed significant results when predicting the willingness to disclose private data. Further results aligned with earlier literature when age was found to be an accurate predictor for the willingness to disclose private data, and when participants presented with an intrinsic trigger were more willing to disclose their data compared to participants who were not presented with any reward. While this study reiterates the power of personalized marketing, it simultaneously highlights the fact that future research should be conducted to gain a deeper understanding of using psychometrics that will likely have a big impact on the world of marketing.

Keywords: personality marketing, psychometrics, self-determination theory, behavioral intent, health data sharing

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List of Abbreviations

ANOVA	Analysis of Variance
BMI	Body Mass Index
CBS	Centraal Bureau voor de Statistiek
CFA	Confirmatory Factor Analysis
GDPR	General Data Protection Regulation
P&C	Property and Casualty
SDT	Self-Determination Theory
UBI	Usage- and Behavior Based Insurance

1. Introduction

With the internet as an integral component of our lives, it has been constantly generating data about our online routines formed through searching and communicating. Researchers show that on Facebook alone, users upload hundreds of terabytes worth of data every single day (Khine & Shun, 2017). Thus, in today's day and age, leaving digital traces and sharing private data is inevitable. Leaving these traces is often necessary to access the full capabilities of a webpage or application, for instance, through the use of cookies. While some people are aware of the fact that their data is being collected, most people unconsciously release their data while browsing in what they assume is a free ecosystem. This data, in turn, is currently being produced at an extraordinarily rapid pace. Khine and Shun (2017) provided an interesting perspective: "Today, people are living in the data age where data become oxygen to people as organizations are producing data more than they can handle" (p. 40). Such private data is extremely valuable for organizations, and experts often refer to this data as 'the new gold' (Forbes, 2019; Deloitte, 2015). With this data, organizations can conduct analyses that can reveal information about their (potential) clients, which firms can use to better position themselves to reach their business objectives (Morey et al., 2015). While some people are aware of how much their data is worth, one may wonder why individuals are willing to give up information that is so prized. Prior studies have explored the willingness to disclose private data, and contrary to rational reasoning, many individuals voluntarily share their personal information in return for short-term benefits (Acquisti & Grossklags, 2005; Blakesly & Yallop, 2020). In recent years, research has shown that consumers are becoming more accepting of the notion of private data collecting (Deloitte, 2015), though an in-depth analysis of what specific aspects play a role in this decision-making process is absent.

1.1. Research problem

In this thesis, two variables that may affect one's willingness to disclose private data are going to be explored. To start, a possible factor that can contribute to data sharing may be someone's personality. An assumption is that individuals who portray certain traits, such as high levels of agreeableness, may be more inclined to abide by data collection initiatives as opposed to individuals who exert low levels of agreeableness. The Big Five Inventory will be used to utilized to categorize personalities (McCrae & Terracciano, 2005). This spectrum of personalities aligns with a relatively new concept, namely personality marketing. This concept is predicted to hold great value in the communications between an organization and the consumer (Matz et al., 2017; Winter et al., 2021). These experts explain that in personality marketing, algorithms align content with an individual's personality traits to ensure the advertisements resonate. Through the use of this marketing strategy, it will be investigated whether certain personalities will be more willing to disclose their private data. A real-life example of market segmentation based on one's personality is the Cambridge Analytica case that occurred between 2010 and 2016. The political consulting firm harvested data obtained from Facebook to target successfully certain individuals based on the Big Five Personality Model through propagandist communications. A former employee explained that the algorithms used could curate a total of 253 predictions that would accurately target groups of people based on their personalities (Hern, 2018). It is implied that Cambridge Analytica's advertising strategies have played a role in the Indian Bihar Assembly Elections in 2010, the Brexit referendum in 2016, and the 2016 U.S. Presidential Election (Granville, 2018).

A second variable that may affect one's willingness to disclose private data pertains to Ryan and Deci's self-determination theory (SDT). This theory states that there are three antecedents of motivation, namely autonomy, competence, and relatedness (Ryan & Deci, 1985). These three universal psychological needs account for reinforcements, such as intrinsic and extrinsic motivators, which may expose the reasoning behind certain decision-making processes.

As data sharing is a broad concept that can vary between sectors, the scope of this research will be narrowed down to one specific sector. While this concept can be applied to any field, a connection will be made to the insurance industry. One reason is that Deloitte (2015) published a report in which they stated that consumers are much more inclined to share private data with insurers versus companies such as Google and Apple. This inherently creates beneficial opportunities for insurers to explore new terrains and conquer new markets. Next, The Boston Consulting Group expressed how the insurance sector is on the verge of a major technological shift in the in-depth report on the evolution and revolution of the insurance industry in a digital world (Hocking et al., 2014). In this report, it is stated that the insurance sector is on the verge of a major technological shift. An entirely digital ecosystem is recommended, which should be driven by private data. These claims reiterate the importance of understanding the phenomenon of data in this market, making it highly suitable to study.

When investigating the insurance sector in the Netherlands there are three main dimensions to investigate, namely, healthcare, property and casualty (P&C), and life. In short, property and casualty insurance refers to the safeguarding of one's belongings (Allstate, n.d.), while life insurance allows persons to designate beneficiaries to individuals who will receive a one-off lump sum payment upon one's death (ABN AMRO, n.d.). In this thesis, the focus will lie on healthcare insurance as a focus group was held to conclude that this scope is most perceptible for this study. In the focus group, it was established that healthcare insurance was favored due to the sheer size of users, and the fact that it is a tangible, mandatory product for all citizens. Healthcare insurance refers to the coverage of costs of visiting a general practitioner, using hospital services, and receiving prescription medication (Rijksoverheid, n.d.). In the Deloitte report (2015) that was mentioned prior, it was found that Dutch survey participants were highly willing to adopt insurance-related services among three products: usage and behavior-based, mobile-based, and risk detection and prevention-based. In this thesis, the focus will lie on usage- and behavior-based insurance (UBI), as consumer interest and the number of insurers introducing UBI propositions are exponentially increasing (Deloitte, 2015). UBI refers to insurance services that are based on a person’s behavior. An example of UBI in healthcare insurance is the a.s.r. Vitality application. In this application, users share their private health data with the Dutch insurance company a.s.r., in return for gift cards or cash back, for instance. By synchronizing health apps, such as Apple Health or Samsung Health, with an activity tracker, like an Apple Watch or a Fitbit, the insurer will receive data on the users’ exercise activities. Beyond sharing their health data synchronized to their smart devices, users can conduct additional health screening tests. For instance, users can complete digital surveys that reveal their lifestyle habits, dietary habits, and whether they smoke or not. Filling out these questionnaires will be compensated with additional points, which users can then exchange for rewards. To take it one step further, users can consult their general practitioner for a consult, for which the user will earn up to 4.000 points (a.s.r. Vitality, n.d.). Such consultations consist of biometrics tests to measure their body mass index (BMI), screen their blood pressure, and run a blood test—which measures cholesterol and glucose levels. While this application is marketed as a health initiative, it essentially is a disguise to collect data. The example demonstrates the marketing strategies that are being implemented to market more efficiently, and in an ethical manner. The aim of this research, and the use of said example, are to better understand the scope of personality marketing and its compatible concepts. Therefore, the research question, which will be answered using a quantitative research method, namely an online experiment, is as followed:

To what extent do certain personality dimensions and the self-determination theory influence the willingness to disclose private data to the insurance sector in The Netherlands?

1.2. Relevance

An important aspect of this thesis is the scientific, managerial, and societal relevance it holds. To start, there is an academic gap within the field of personality-based communications. While some research in this area, such as the effect of personality marketing on marketing outcomes with tangible products, has been conducted (Hirsh et al., 2012; Matz et al., 2017; Winter et al., 2021), there are still numerous elements that require further examination. However, there is still a void of research in other sectors, such as the financial industry. This research, therefore, attempts to fill the academic gap and aims to further explore possibilities within the field of personality-based communications.

Next, regarding managerial relevance, this study aims to highlight possible economic benefits for organizations to increase their efficiency with regard to customer communications. This study can help businesses better understand the utilization of personality marketing so that they can personalize advertisements to each individual. Ultimately, this marketing approach can help them achieve their business objectives, as research has shown that personalization can increase click-through rates (Bleier & Eisenbeiss, 2015), and thus become more profitable.

Lastly, regarding societal relevance, the number of people who own smart devices only continues to increase, thus it can be implied that the datafication that is associated with digitalization will only surge. More organizations are tugging on individuals to share their data, and the limited understanding of consequences associated with releasing private data makes it child's play for organizations to obtain this data. The UBI techniques mentioned prior are merely examples of applications that have been caught on by the public, and there are many more to come. While this surge will likely be beneficial, it is also crucial to recognize the possible threats to the society that may transpire (Clark & Calli, 2014; Matz et al., 2017). Therefore, it is crucial to present a discussion based on integrity and scientific evidence to gain a comprehensive understanding of these new concepts and strategies.

1.3. Outline

This thesis will be divided into five chapters, with Chapter 2 being a literature review of empirical research that provides an encompassing overview of theory regarding the research topic. Chapter 3 will present the methodology of this study, including the justification for the used research method, operationalization of variables, and consideration of reliability and validity. Then, in Chapter 4, the results of the experiment will be presented as the established hypotheses will be attended to. An independent samples t-test, a multiple regression, and a one-way between-subjects analysis of variance (ANOVA) are amongst the analyses that will be conducted to interpret the obtained data. Lastly, in Chapter 5, a discussion and conclusion are presented that critically analyses the evidence found in the prior chapter while also addressing implications, limitations, and suggestions for further research.

2. Theoretical framework

In this chapter, multiple concepts that shape this research are discussed. To start, a brief examination of the topics of digitization, datafication, and privacy is presented. Data is an incredibly complex notion, and for the pertinence of this research, merely essential concepts to better illustrate the foundation of this research are provided. Then, theories on why individuals are willing to share data are explained, in which a connection to Ryan and Deci's self-determination theory (1985) is made. Lastly, the concepts of personalized marketing and personality marketing are presented.

2.1. Digitization and datafication

Both societies and organizations have reaped the benefits of technological advancements in the past decades. This includes, but is not limited to, being able to communicate globally at a rapid pace, having access to efficient information retrieval, and being able to use technologies, such as analytics, in business spheres (Johnson & Wetmore, 2021). These advancements will only continue to progress as only technology will cease to develop and extend. With that being said, businesses must adjust their business models to facilitate the technological shift to use it to an organization's advantage (Loebbecke & Picot, 2015). In order to remain a notable player in any competitive market, organizations must keep up with these advancements. Therefore, the most valuable approach is to invest in data. Several large firms have claimed data to be the new gold, and the amounts of data that are available are increasing exponentially (Forbes, 2019; Deloitte, 2015). While data is a broad concept that is used in many different fields, in this study the focus will lie on private data. The European Parliament of the Council (2015) defines private data as any information concerning a distinguishable individual in reference to one or more factors, specific to their tangible and intangible identity. This includes their physical existence, but also their social and economic existence.

With the emergence of smart devices, unfathomable amounts of private data are being produced each day. For instance, Cuenca et al. (2021) state that, on Facebook alone, there are over five million comments published and at least 1.5 million photos uploaded on the platform each minute. Humans have turned into "walking data generators" (McAfee & Brynjolfsson, 2012, p.5), and it has become impossible for traditional data-processing systems to process this data due to the sheer volume of data generated (Provost & Fawcett, 2013). While the term 'big data' has taken the world by storm, even experts are divided about its formal definition. Mayer-Schönberger and Cukier (2013) define big data as large-scale data sets that hold information that cannot be obtained through regular-sized data sets. Counter to this definition, others refer to big data with the 'several Vs' interpretation. In research by Favretto et al. (2020), multiple professionals in the field were interviewed to provide a consolidated, unified definition, in which they agreed on the four Vs: volume, variety, velocity, and veracity. Both definitions by Mayer-

Schönberger and Cukier (2013) and Favretto et al. (2020) congregate nicely in a definition provided by Khine and Shun (2017), in which they refer to big data as large volumes of digital data that need diverse sorts of velocity depending on the application domain. These domains hold many data types and sources and their execution will depend on the environment in which it is implemented. It is believed that this definition is an encompassing interpretation, as these researchers have all emphasized the importance of adopting a flexible understanding of the notion of big data.

The benefits of using data have been demonstrated numerous times (Chen et al., 2012; Khine & Shun, 2017). Chen et al. (2012) state that using big data analytics and data-driven decision-making helps organizations reconstruct their business and gain an edge over their competition. Additionally, Khine and Shun (2017) describe that big data does not only allow for increased efficiency in firms, they also claim that big data will be comparable to the "digital nervous system" for organizations.

2.2. Privacy

Although businesses would prefer to obtain all possible data points on as many individuals as possible, privacy laws refrain them from doing so. In 1890, Warren and Brandeis defined privacy as "the right to be let alone" (p. 195). Katsikas et al. (2005) suggest the definition of privacy to be that it is a person's own right to decide whether and to what degree private data is made public. In 2016, the European Union adopted its first data protection package which stipulated that EU citizens have the right to have their private data protected (European Commission, n.d.). In addition to protection from the European Commission, individuals themselves are incentivized to carefully decide whether they want to voluntarily provide private data.

The main concern surrounding private data sharing and ensuring a person's privacy is ethics. With the surge of digitization and datafication, society requires researchers in all scopes to work together to address these ethical challenges (Favaretto et al., 2020). These researchers additionally note that big data, for instance, present issues such as the absence of respect for personal identity, lack of informed consent, and possibly discrimination. Lippert and Swiercz (2007) support these arguments and add that data sharing should occur in an acceptable practice through the just nature of data sharing, and to what extent individuals will be guarded against ethical violations.

Data collection can transpire in two different manners, namely overt and covert (Aïmeur & Lafond, 2013). With organizations thoroughly aware of the value of private data, they would prefer to obtain all possible data points of their (potential) customers. However, due to the legal right to privacy (Gavinson, 1995), it is illegal for organizations to scrape data without users' consent. Thus, with regard to both the law and ethics, most data collection takes place in an overt manner which entails that individuals are aware of the fact that their data is being collected (Aïmeur & Lafond, 2013). For instance, users have to accept HTTP cookies before accessing a website, which provides personalized access to websites and/or applications (Kristol, 2001). While allowing for a personalized experience for the user, organizations and third parties also reap benefits from cookies, as they use them to track visitors and their online behaviors (Cahn et al., 2016). The second example of overt data collection is the a.s.r. Vitality application that was discussed in the previous chapter. Users using this application are aware of the fact that their private health data is being collected, though it is suggested that in their privacy calculus the benefits (e.g., cashback) outweighed the costs. While a.s.r. reiterates on their website and in their terms and conditions that users voluntarily agree to share their private health data, users are often not aware of what they are agreeing to due to the concept of bounded reality. This concept illustrates that individuals are simply unable to process the complex consequences associated with the release of personal information (Acquisti & Grossklags, 2005). Thus, intuitive bounded rationality limits one's understanding to process significant information, for which they use simplified mental models to make a rational decision. In a.s.r. Vitality's case, users will receive a gift card worth five euros each week if they meet their activity goals, but what users likely are not aware of is that their data will be stored for up to seven years (a.s.r. Vitality, n.d.). This example perfectly demonstrates Acquisti and Grossklags' (2005) theory to a real-world example, as their research showed that individuals are willing to exchange long-term privacy for short-term benefits. With this being said, even in overt data collection, the specifics are often hidden in difficult-to-read terms and conditions, making it even more difficult for users to understand what data companies obtain, and how much they obtain (Rossetti et al., 2020).

Covert data collection transpires when the data collection appears hidden for either an individual or a collective group (Petrovic & Djordjevic, 2015). Alas, this approach occurs frequently. While many speculate about the amounts of data social media giants obtain, it has recently come to light that Facebook has roughly five thousand data points of every user on the application (Isaak & Hanna, 2018). When European data protection supervisor, Buttarelli, was asked about Facebook's data collection, he stated that "every single action, every single relationship is carefully monitored" (Singer, 2018). While it is sensible that Facebook collects private data, the majority of its users do not realize how much data is being collected. The challenge, therefore, concerns the protection of sensitive information from abuse (Lippert & Swiercz, 2007). Even with a personalized advertisement, experts argue that such levels of personalization may lead to the exploiting of individuals without their knowing (Bodó et al., 2017).

The Cambridge Analytica case, addressed in Chapter 1, shows just how powerful personalized targeting can be, while simultaneously highlighting the possible risks it can accompany (Osborne, 2018). In 2013, Alexandr Kogan curated and launched an application called 'thisisyourdigitallife', a personality survey disguised as a tool to scrape private data (Granville, 2018). By using the data this application produced, Kogan gained insight into 320,000 user profiles that he then sold to consulting firm Cambridge

Analytica (Schneble et al., 2018). It is important to note that users of Kogan's application did not consent to their data being passed onto Cambridge Analytica. The illegal activities did not end there, as additional private data were obtained from roughly fifty million people, all without their consent (Cuenca et al., 2021). Examples of acquired data are users' identities, friend networks, Facebook 'likes', personality traits, and even voter records (Hern, 2018). Big data helped built algorithms that were able to identify the personalities of American voters, and were able to successfully influence their voting behavior through psychological manipulation (Granville, 2018). Former Cambridge Analytica employee, Christopher Wylie, stepped forward to publicize the true nature of the consultancy firm (Hern, 2018). Wylie provided examples of how the firm employed personality marketing to persuade certain Facebook users in an interview with The Guardian and stated the following:

> (...) It was targeting conscientious people. It was a picture of a dictionary and it said 'Look up marriage and get back to me'. For someone who is conscientious, it is a compelling message. A dictionary is a source of order, and a conscientious person is more deferential to structure. (Hern, 2018, para. 25)

Wylie then further explains that the algorithm that was built by Cambridge Analytica employees could curate 253 predictions that would help accurately target different groups, based on one's personalities. For example, a neurotic and extroverted Democrat would have been shown another advertisement than an emotionally stable, introverted individual, thus designing advertisements to align with their inclination to vote (Hern, 2018). In late 2018, investigations were opened by the Federal Trade Commission, and Cambridge Analytica filed for Chapter 7 Bankruptcy in 2019 (Hern, 2018; Scott, 2019). After the investigations, the European Union came together to ensure such an incident would not reoccur. As a result, the European General Data Protection Regulation (GDPR) was introduced. This law shows a paradigm of security, in which, inter alia, it grants individuals easy access to their own data and allows them to request organizations to delete their data (Chassang, 2017). As mentioned prior, while this case may be a distressing example of what can happen when access to such data falls into immoral hands, it does show the prominence of personality marketing.

2.3. Motivation and behavioral intent

Multiple experts have studied the phenomenon of the willingness to disclose their private data (Bhatnagar & Kumra, 2020; Lippert & Swiercz, 2007). Psychologists argue that there always is an incentive behind every action and that without motivation action will not get carried out (Beckmann & Heckhausen, 2018). In psychology, motivation refers to the "initiation, direction, intensity, and persistence of behavior" (Brown, 2007, p. 4) and the "energy, direction, persistence and equifinality— all aspects of activation and intention" (Ryan & Deci, 2017, p. 69). The self-determination theory developed by Ryan and Deci (1985) describes human motivation and psychometrics using empirical theories. This approach indicates three innate psychological needs that are the basis for self-motivation, namely the need for autonomy, competence, and relatedness. Autonomy refers to people's primary need to be in control of their physical and mental environment. More specifically, this need relates to the psychological urge to sense self-determination and to approve the cause of behavior as one's own (Cerasoli et al., 2016). These researchers further state that competence refers to the drive to demonstrate and improve one's abilities. Satisfaction of competence needs may predict performance outcomes, as one's needs to demonstrate their competence is fundamentally gratifying. Lastly, relatedness refers to the desire to be respected and valued by others that are important to oneself. Such desires are also noted in the hierarchy of needs theory (Maslow, 1943) and in the existence-relatedness-growth theory (Alderfer, 1969).

Essentially, the self-determination theory suggests that individuals should have an incentive to participate in any transaction. These incentives, referred to as motivations, can be divided into two dimensions: intrinsic and extrinsic motivations. The first relates to the individual's desire to perform the task for one's own sake, that is to derive purpose, enjoyment, or fun from the activity, while the latter relates to contingent rewards that serve as positive reinforces, such as praise, rewards, or punishment (Benabou & Tirole, 2003). According to Ryan and Deci (2017), these motivations are a continuum. The relative left displays non-self-determined behavior, in which there is no motivation, whether that be through non-valuing regulatory processes or incompetence. In the center, extrinsic motivation is displayed, for which an extraneous variable needs to be presented to affect motivation. On the relative right, behavior is self-determined, which can be associated with intrinsic motivation. Furthermore, Ryan and Deci suggest that extrinsic motivation can affect external regulation (e.g., compliance and external rewards), introjected regulation (e.g., self-control, ego-involvement), identified regulation (e.g., personal importance, conscious valuing), and integrated regulation (e.g., awareness). On the other end, intrinsic motivation can affect intrinsic regulation (e.g., interest, enjoyment, inherent satisfaction, congruence, synthesis with self). While Deci (1971) conducted the first laboratory experiment on motivation, many psychologists followed their path and found evidence for the effects of motivation. For instance, Killeen (1982) found that, generally, people are primarily extrinsically motivated. This infers that they are more likely to be motivated when they are presented with a tangible reward, as opposed to an intrinsic trigger. Cameron and Pierce (1994) found that verbal rewards, such as praise, increase intrinsic motivation. Lastly, it is important to note that one cannot simply present any reward in any situation and assume that motivation will be derived from that reward. For instance, intrinsic motivation can decrease when an individual is presented with an extrinsic reward, as one may feel that their actions are disvalued and not worthwhile (Covington, 2002). Therefore, rewards in any situation should be considered attentively.

As businesses are hoping to obtain big data, to then execute personalized marketing, the goal is to understand what drives individuals to be willing to disclose their private data. This concept can be measured through behavioral intent, which looks at the consideration between potential benefits and perceived risks of disclosing private data (Xu et al., 2011). While both of these concepts are used in the conceptual model, the focus will lie on the willingness to disclose private data. Lippert and Swiercz (2007) provide insight as to why individuals are willing to share their private data: fulfilling the requirement of an economic transition, making an emotional connection, signifying trust, and lastly, reducing ambiguity. Lippert and Swiercz further claim that while the internet is maturing, so are its users, and installing a sense of trust during the data collection process is crucial to maintaining sustainable mediated transactions. Bhatnagar and Kumra (2020) build on these motivations and provide more arguments for private data sharing: to help others, to expect remuneration, and to abide by moral obligations. Multiple times, researchers have found that individuals find these motivations compelling and that even with adequate information to make privacy-sensitive decisions, they are willing to exchange long-term privacy for short-term benefits (Acquisti & Grossklags, 2005). More specifically, in this study, it was mentioned that 41 percent of respondents acknowledged having high privacy concerns while rarely reading privacy policies. In this same study by Acquisti and Grossklags (2005), 21.8 percent of respondents admitted to having shared their social security number for discounts or better recommendations.

These findings discussed prior implicate that while groups of people may appear hesitant to release personal information, they are inclined to abandon their principles once a reward is presented. It can, therefore, be inferred that when presented with a reward, individuals are more willing to disclose their private data. Then, it is crucial to investigate what kind of reward is more effective in altering one's behavioral intent. While studies found that intrinsic motivation is inherently more powerful than extrinsic behavior (Clanton-Harpine, 2015), more individuals are primarily extrinsically motivated (Killeen, 1982). With that being said, it is predicted that people are more likely to get triggered by the presence of an extrinsic reward, thus the following hypothesis is constructed:

H1 *Participants will be more willing to disclose private data when receiving an extrinsic reward compared to participants who are presented with an intrinsic trigger*

2.4. Personalized marketing

As the trace of data that people leave online is being absorbed by organizations, advertisers can then use this data to their advantage. Advertisers have access to this wide range of data, whether that is demographic data, information on their interests, location, and much more (Smit et al., 2014). This data are not only derived from cookies, but also from every search, click, and purchase. Not just advertisers make use of personalized marketing, but search engines such as Google and Yahoo are also monetizing their ad spaces based on user queries (Khine & Shun, 2017). Algorithms can use data to individually determine what ads are shown, and what information is made accessible (Cheney-Loppold, 2017). This emerging strategic approach is called *mass customization* or *personalization*, in which elements of the marketing mix are individually selected for each person (Goldsmith & Freiden, 2004). Personalized marketing is such a valuable strategy as the combination of information made available through collected data and the flexibility in production can tailor communications to what may appeal to different individuals. Recent studies have proven the efficiency of personalized marketing and state that it is much more profitable to employ this marketing strategy (Dijkstra, 2008; Goldsmith & Freiden, 2004; Shen, 2014). Proof of these efficiencies can be found beyond academic literature. Large companies tailor their products and services to their customers through data-driven campaigns, improving customer experiences through personalized content. Clear examples include the viewing recommendations streaming services offer, and product suggestions by e-commerce retailers.

While consumers acknowledge the benefits of personalization, such as being exposed to personally relevant communications, which equates to receiving a better preference match, service, communication, and oftentimes a better overall experience (Vesanen, 2007), a paradox continues to exist. The personalization paradox (Awad & Krishnan, 2006) refers to the finely balanced perceived positive and negative effects of personalization. In a study by Strycharz et al. (2019), it was found that in a sample of 324 participants, most acknowledged the benefits of personalization as personal relevance, convenience, and a higher brand relatedness as well as economic benefits by being provided with coupons. On the other hand, these same participants identified concerns with personalization, such as a sense of vulnerability and intrusiveness, lack of agency, and feelings of manipulation. These concerns can cause a chilling effect, in which the recipient of the communication can feel as if they are being watched, disrupting their privacy (Sahni et al., 2018). Therefore, advertisers must acknowledge the paradox to ensure a suitable benchmark for individuals to prevent negative feelings from arising.

If advertisers want to take it one step further, a relatively new concept in personalized marketing is personality marketing. In this concept, consumers are shown content that is in consonance with their personality, measured by psychometrics, which help accurately market different services and products to intended target audiences (Winter et al., 2021). There may be initial skepticism surrounding this concept, but Youyou et al. (2015) showed that users' Facebook 'likes' can be used to accurately predict users' personality traits with higher precision than when estimations were made by close friends. This was conducted by employing machine-learning techniques which extracted data from a personality survey. In one of the first studies investigating personality marketing, Hirsh et al. (2012) conducted an experiment to match communications with the participant's personality traits. Subjects were shown different advertisements for a smartphone and were then questioned whether there was a favourability towards a specific advertisement. Examples of the different messages include ‘With the new XPhone, you’ll never miss an important message, simplifying your work life’ to trigger participants with high levels of conscientiousness. To prompt participants with high levels of extraversion, the tagline ‘With the new XPhone, you will always be where the excitement is’. Results showed that one’s focal personality traits were significant predictors of the favourability of one of the advertisements.

In 2017, Matz et al. conducted a large-scale psychological persuasion experiment with a sample of 3.7 million participants. The researchers gained insight into users’ Facebook Likes, leaving a wide array of their private data. With this data, personality profiles were mapped out and then used to match advertisements relating to the interests of the participant. For instance, subjects who showed high levels of extraversion were shown an advertisement of a woman dancing in a nightclub, with the description ‘dance like no one’s watching’. On the other end of the spectrum, subjects who showed low levels of extraversion were shown an advertisement of a woman applying makeup in her bathroom, with the description ‘beauty doesn’t have to shout’. Results found that when participants were shown advertisements in consonance with their personality traits, it resulted in up to 40 percent higher conversion rates. Therefore, it can be suggested that employing the strategy of personality marketing appeals to the psychological needs of target audiences, and thus, positively affects marketing metrics.

A more recent study conducted by Winter et al. in 2021, similar to prior research by Hirsh et al. (2012) explored the relationship between personality marketing and product advertisements. In the experiment, five different advertisements were curated for a smartphone, in which each of the five ads would align with one of the five Big Five personality traits. For participants with high levels of extraversion, they showed a picture of a woman in a nightclub, taking a selfie with her friends, and captioned it as ‘Sensa Phone: Designed for those who follow the excitement’. Results differed from previous studies as no significant findings were derived from the experiment with regard to personalized marketing, however, the successful operationalization of concepts in this study is valuable nonetheless.

In this thesis, the Big Five Inventory will be used to define and categorize personalities to use as psychometrics. The five dimensions in this model are openness, conscientiousness, extraversion, agreeableness, and neuroticism (McCrae & Terracciano, 2005). This model is often referred to as the ‘OCEAN’ model, an acronym for the five personality dimensions. To surpass surface-level research, the decision has been made to investigate three of the five proposed personality dimensions, namely agreeableness, conscientiousness, and neuroticism. These three dimensions have been chosen based on prior research by Bhatnagar and Kumra (2020) and Lippert and Swiercz (2007), as they provide a reference point for the links between personality dimensions and the willingness to disclose private data.

These personality dimensions will be investigated on a spectrum, meaning that an individual can either score high or low on each separate spectrum.

When referring to agreeableness, experts often refer to cooperation, trustworthiness, and being good-natured (Loehlin et al., 1998). Additionally, it is highly compatible with conformity values, meaning that individuals with high levels of agreeableness prefer not to violate norms or upset others. Individuals who score high on agreeableness, therefore, tend to be “good-natured, compliant, modest, gentle and cooperative” (Roccas et al., 2002, p. 792). On the other end of the spectrum, individuals who score low on agreeableness tend to be “irritable, ruthless, suspicious, and inflexible” (p. 792). Bhatnagar and Kumra (2020) state that the enjoyment of helping, similar to the concept of altruism, ties in with this personality dimension appropriately. With that being said, the following hypothesis is proposed:

H2a *There is a positive relationship between agreeableness and willingness to disclose private data*

The conceptual model of this thesis is based on an interaction effect, meaning that the joint effect of two variables, namely psychometrics and a specific reward that triggers motivation, is significantly greater than the sum of their parts (Lavrakas, 2008). It is hypothesized that someone’s behavioral intent varies per personality, and in turn strengthened by the presentation of a specific reward. Either reward will strengthen the relationship between agreeableness and behavioral intent, as they are inherently compliant and cooperative, regardless of which reward is presented. Therefore, the following hypothesis is presented:

H2b *The relationship between agreeableness on willingness to disclose private data is moderated by a reward*

Next, conscientiousness refers to competence, thoughtfulness, and self-discipline. Individuals who score high on conscientiousness tend to be “careful, thorough, responsible, organized, and scrupulous” (Roccas et al., 2002, p. 793). Additionally, these individuals are likely to have a high motivation to achieve goals that are important to them (Gosling et al., 2003). On the other end of the spectrum, individuals who score low on conscientiousness tend to be “irresponsible, disorganized, and unscrupulous” (p. 793), and often display impulsive behaviors. The act of fulfilling moral obligations, as proposed by Lippert and Swiercz (2007) aligns with this conscientiousness accurately. It is anticipated that participants who show high conscientiousness will be more considerate of personal innovativeness (Bhatnagar & Kumra, 2020). With regard to the moderation effect, it is expected that conscientious individuals judge with reason and are more organized, which is hypothesized to result in increased intrinsic motivation. This interaction effect can ultimately affect the main effect, therefore the following hypotheses are proposed:

H3a *There is a positive relationship between conscientiousness and willingness to disclose private data*

H3b *The relationship between conscientiousness on willingness to disclose private data is moderated by a reward*

For the final personality dimension, neuroticism, experts often refer to the trait disposition that experiences negative effects, such as anger, anxiety, self-consciousness, or emotional instability (Widiger & Oltmanns, 2017). Individuals who score high on neuroticism tend to be "anxious, depressed, angry, and insecure" (Roccas et al., 2002, p. 793). On the other end of the spectrum, individuals who score low on neuroticism tend to be "calm, poised, and emotionally stable" (p. 793). The interaction effect is expected to demonstrate that intrinsic triggers can influence the behavioral intent of neurotic individuals. Theory shows that high levels of psychological well-being were indicators of intrinsically rewarding experiences (Graef et al., 1983). It is thus expected that these individuals are more likely to disclose private data when exposed to an intrinsic trigger. In order to test assumptions and confirm prior findings, the final two hypotheses are as followed:

H4a *There is a positive effect between neuroticism and willingness to disclose private data*

H4b *The effect of neuroticism on willingness to disclose private data is moderated by a reward*

The preceding hypotheses are constructed to gain insight into the outcome variable of willingness to disclose private data. However, the contrary aspect, perceived risk, has not yet been explored. Therefore, H5 aims to unveil significant findings regarding the relationship between someone's personality and how they acknowledge potential risks of data sharing. While there are two more personality variables in this research, conscientiousness was chosen deliberately. This variable, which refers to a person's sense of care and responsibility, is hypothesized to have a significant relationship with perceived risk. Individuals who score high on this personality spectrum are assumed to have a strong sense of awareness, thus being more likely to grasp possible risks of data sharing. The constructed hypothesis is as followed:

H5 *There is a positive effect between conscientiousness and acknowledging potential risks of data sharing*

The last set of hypotheses apply to demographic variables, age, and educational level. Prior research has explored the relationship of these two variables on behavioral intent to a certain degree, in hopes of better understanding the dynamics to increase the efficiency and effectiveness of healthcare management in the digital age. To start, Malhotra et al. (2004), conducted an experimental study in which participants were asked to report on their willingness to disclose private data in a consumer setting, where they found a significant negative relationship between age and behavioral intent. A second study with identical variables, conducted by Kim and Choi (2019), took place in the health care sector with a sample consisting of older adults. Findings primarily showed that older adults were more selective about sharing their private data, thus confirming the negative relationship. Additional findings from this study show that older adults have relatively low levels of trust in government agencies regarding their likelihood to share their private information. This result estimates that there may be a possible correlation between age and perceived risk. To explore the relationship between age and behavioral intent further, the following hypotheses are constructed:

H6a *There is a negative relationship between age and willingness to disclose private data*

H6b *There is a positive relationship between age and perceived risk to disclose private data*

The second demographic variable that may have a significant relationship with behavioral intent is educational level. Referring back to Kim and Choi's (2019) study, they found a significant negative relationship between education and an adult's willingness to share private data. When looking at the other end of the behavioral intent measure, Malhotra et al. (2004) discovered a significant negative relationship between educational level and trusting beliefs. Moreover, Phelps et al. (2000) found a significant relationship between education and privacy concerns. While no conclusions can be drawn on perceived risk, as different measures are used, it can be inferred that both trusting beliefs and privacy concerns can relate to perceived risk. To find whether these findings will transfer to this research, the following hypotheses will be answered:

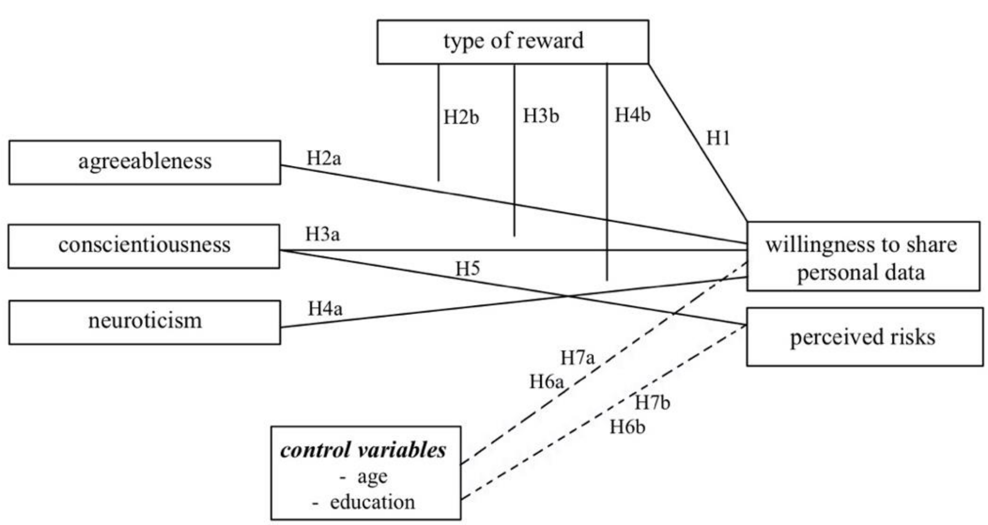
H7a *There is a negative relationship between educational level and willingness to disclose private data*

H7b *There is a positive relationship between educational level and perceived risks to disclose private data*

All variables used in this research, along with their corresponding hypotheses, are presented in Figure 1. In the following chapter, Chapter 3, the methodology and operationalization of variables are discussed.

Figure 1

Conceptual model



3. Methodology

After having presented a set of twelve hypotheses and the conceptual model, this chapter describes the research design, the measurement of concepts, the experimental procedure, the sample and sampling techniques, and the approach to data analysis. To close, reliability and validity will be discussed.

3.1. Research Design

Quantitative research will be used to answer the proposed research question, as it allows for accurate observation and examination of objective data (Schilderman, 2014). This research method is often conducted in a deductive manner, meaning that the hypotheses presented are based on existing concepts and theories (Wilson, 2014). Additionally, this research will also use a bottom-up approach, as it will act as explorative research to help better understand a developing concept of personality marketing (Fallon, 2016). These combined approaches permit an appropriate research method that establishes a promising framework for this thesis.

An online experiment will be conducted to collect data that allows for the testing and refining of concepts and theories, as well as making possible predictions about future events (Vargas et al., 2017). Conducting an online experiment is the most appropriate tool for this study as it considers the exploration of cause-and-effect relationships and correlations between variables (Neuman, 2014). An online experiment has many benefits, as it recognizes a diverse sample population, more generalizable results, and a fast theory to experiment cycle (Huber & Gajos, 2020). Additionally, this experimental method allows for high convenience and accessibility for participants, making it more inviting to partake in the experiment. While recent technological advancements have made it possible to conduct field experiments online, a major issue that arises with this experimental method is the absence of receiving informed consent from participants. Therefore, it is not feasible to construct an ethical study with regard to time and resource restraints. Therefore, an online experiment is the most suitable quantitative research tool for this study.

The research design for this experiment is a true experimental design with three experimental questions. In the experiment, each participant will be randomly assigned to one condition. Additionally, they will be exposed to three scenarios, in which they will be asked to report on their behavioral intent on sharing their data with a hypothetical health insurer. The randomization, which will be the remuneration for sharing one's private data, will be based on rewards derived from the self-determination theory (Ryan & Deci, 1985). The control group will receive no remuneration. The first experimental condition will be presented with a fictional extrinsic reward, and the second experimental condition will be presented with an intrinsic trigger. After the first block, participants will be asked to report on three personalities based on items from the Big Five Personality Index developed by Fiske (1949). While a more detailed sample description will be provided in section 3.4.1, it is worth noting that the sample will consist entirely of Dutch citizens. Therefore, the experiment will be presented in the Dutch language.

3.2. Research Variables and Measures

This section of the chapter contains the measures for items used to evaluate variables that appear in the conceptual model. Later, the justification of scales and measures used will be discussed.

3.2.1. Behavioral Intent

As mentioned prior, this research aims to study an individual's willingness to disclose private data. The willingness of individuals to release said data can be measured through behavioral intent. Oliver (1977) describes this concept as the reflection of an individual's intent to engage in a specific behavior. Reporting one's attitudes and actions in a survey is a delicate process that requires carefully constructed items to obtain accurate data, thus is it crucial that such concepts are measured in a comprising manner (Acquisti & Grossklags, 2005). Using validated scales from experts is recommended to increase the likelihood of constructing a valid study. While in this specific field of research there are no scales that can be used verbatim to measure behavioral intent in sharing private data, some studies have investigated this concept in the realm of information technology.

Providing a comprehensive overview of how researchers have employed behavioral intent throughout different studies is relevant and adds to the validity of this variable. To start, Lam et al. (2007) have examined behavioral intent toward the adoption of information technology. To measure behavioral intent, they explored concepts such as self-efficacy, subjective norms, perceived beliefs, and task-technology fit and how they were positively related to behavioral intent. Next, Hou (2014) investigated user acceptance of business intelligence systems by studying users' intentions to adopt such systems. Hou presented different concepts, which consisted of perceived usefulness, attitude toward use, usage behavior, and self-efficacy to measure behavioral intent. Then, in 2019, Chao studied the behavioral intent of participants to use mobile learning applications. In this research, Chao used performance expectancy, effort expectancy, and social influence to measure behavioral intent. The commonality between these studies is that they all use a sum of separate constructs to measure behavioral intent. These three scales were not used in this thesis, they were rather utilized to justify the scale that was used for this study.

Most similar to this study, Xu et al. (2011) have validated a scale that presents four concepts that encompass behavioral intent, with three contributing to overall willingness, and one referring to perceived risk. Perceived value (Items BIW1, BIW2), perceived benefit (Item BIW3), and willingness to disclose data (Items BIW4, BIW5) make up the overall willingness, while perceived risks consists of two items (BIR6, BIR7). In this equation, which is weighted to prevent some data to contribute more weight than others, one measures whether the benefits of sharing personal information (i.e. personalization) overwhelm the risks and consequences associated (i.e. privacy concerns) (Kokolakis, 2017; Xu et al., 2011; Wang et al., 2016). The questionnaire, including a full list of each item in each scenario, is presented in Appendix A and B. This scale is adapted as it has been validated, with perceived value being (α = .86), perceived benefit (α = .90), willingness to disclose (α = .97), and perceived risk (α = .91), thus internal reliability is assured as they exceed .70 (Saunders et al., 2016).The items in this scale are measured on a 7-point Likert scale, from *strongly disagree* to *strongly agree*. A Likert scale using seven points allows for a wider range for participants to accurately choose their responses, and are often used in human-behavior experiments to obtain more nuanced and richer data (Nunnally, 1978). Each item will be adjusted to each individual scenario so that they correspond with the text of the question.

Table 3.1

Items used to measure Behavioral Intent, adopted from Xu et al. (2011).

Original Item Measurement	**Updated Item Measurement**	**Item Code**
I think the risks of my information disclosure will be greater than the benefits gained from the use of M-Coupon service.	I think the benefits gained from sharing data outweigh the risks of my disclosure.	BIW1
I think the risks of my information disclosure will be greater than the benefits gained from the use of M-Coupon service.	I think the risk of my disclosure will be greater than the benefits gained from sharing this data. *(R)*	BIW2
Overall, I feel that using M-Coupon service is beneficial.	Overall, I feel that sharing this data will be beneficial.	BIW3
How interested would you be in having your personal information (including your location) used in the M-Coupon service?	I am interested to share this data in return for this reward.	BIW4
How likely would you provide your personal information (including your location) to use the M-Coupon service?	If I could, I would share this data in return for this reward.	BIW5
Providing the service provider with my personal information would involve many unexpected problems.	Providing the insurer with my personal data would involve many unexpected problems.	BIR6
It would be risky to disclose my personal information to the service provider.	It would be risky to disclose my personal information to the insurer.	BIR7

3.2.2. Personalities

The second concept that will be measured during the online experiment are psychometrics. To operationalize this concept, the Big Five Personality Index (Fiske, 1949; Loehlin et al., 1998) will be used. While the original scale consists of 44 items and tests participants on five personality traits, the scale is adjusted slightly to better reflect the objective of this study. A total of 26 items will be presented, of which eight items will be asked relating to conscientiousness (Items PC1; PC8), nine items will be asked relating to agreeableness (Items PA1; PA9), and eight items will be asked relating to neuroticism (Items PN1; PN8).

Participants will be asked to complete a series of questions that start with the statement "I see myself as someone who..." on a 7-point Likert scale, ranging from *strongly disagree* to *strongly agree*. A participant can score high or low on either of these traits, meaning that the results of these items will provide a spectrum of personalities. If a participant were to score high on conscientiousness, it would mean that the participant is disciplined and organized, whereas scoring low would infer that the participant is impulsive and careless. Sample items are '...does a thorough job' and '...is a reliable worker'. If a participant scores high on agreeableness, it would mean that the participant is helpful and empathetic, while scoring low would mean that they are uncooperative and suspicious. Sample items are '...has a forgiving nature' and '...likes to cooperate with others'. Lastly, scoring high on neuroticism would mean that the participant is anxious and prone to negative emotions, whereas if they scored low they would be calm and secure. Sample items for the last personality dimension include '...can be tense' and '...worries a lot'.

Table 3.2

Items used to measure Personality (Agreeableness, Conscientiousness, and Neuroticism), adopted from John and Srivastava (1999).

Original Item Measurement	Code Item	Original Item Measurement	Code Item
Does a thorough job	PC1		
Can be somewhat careless *(R)*	PC2	Can be cold and aloof *(R)*	PA6
Is a reliable worker	PC3	Is considerate and kind to almost everyone	PA7
Tends to be disorganized *(R)*	PC4	Is sometimes rude to others *(R)*	PA8
Tends to be lazy *(R)*	PC5	Likes to cooperate with others	PA9
Perseveres until the task is finished	PC6	Is depressed, blue	PN1
Makes plans and follows through with them	PC7	Is relaxed, handles stress well *(R)*	PN2
Is easily distracted *(R)*	PC8	Can be tense	PN3
Tends to find fault with others *(R)*	PA1	Worries a lot	PN4
Is helpful and unselfish with others	PA2	Is emotionally stable, not easily upset *(R)*	PN5
Starts quarrels with others *(R)*	PA3	Can be moody	PN6
Has a forgiving nature	PA4	Remains calm in tense situations *(R)*	PN7
Is generally trusting	PA5	Gets nervous easily	PN8

3.2.3. Control Variables

Some demographic information of participants, including age and educational level, will be taken into account as the control variables. Both variables will be measured as categorical variables. Control variables are a central element of the research design. Confounding variables are likely to covary with the hypothesized focal independent variables, thus limiting both the clarification of causal inference as well as the explanatory power of the model (Stone-Romero, 2009). Therefore, experts should aim to eliminate threats to inferences to decide which focal independent variables should be hypothesized. This is typically done by including, or controlling for, extraneous variables that are deemed theoretically important, but are not focal variables of the study (Kish, 1959).

3.3. Procedure and Experimental Manipulation

The construction for the online survey was built in Qualtrics, a reliable tool that allows for the automatic storing of data and randomization of variables (Saunders et al., 2016). Prior to creating the experiment, a small focus group was held with three professionals in the field of insurance. As there are three main scopes of insurance in the Netherlands, it is important to choose one scope for this study that would best resonate with the population sample. After speaking with three professionals employed at Nationale Nederlanden, one of the biggest insurers in the Netherlands, it was determined that health insurance is the most evident scope, as every Dutch citizen is a consumer of this insurance product. When looking at life insurance, for instance, many citizens may not see the urgency to become a consumer of such a product, as their pension still may be years and years away. When discussing the scope of P&C with experts, it was stated that there are already many studies being conducted as of right now with regard to telematics, thus making health insurance most advantageous to investigate. A summary of methodological decisions made for this focus group and findings discovered are presented in Appendix C. After having conducted the focus group, a survey was constructed and pretested to verify the comprehensibility of items and the overall length of the experiment.

3.3.1. The Pretest and Adjustments

The pretest was conducted with 18 participants through a method of convenience sampling. Participants were asked to report on their overall experience and more specific aspects such as understandability, exhaustiveness, and convenience. As a result of the pretest, several changes were made to the questionnaire. To start, the experiment was shortened from five hypothetical scenarios to three. In the pretest, participants were asked about their behavioral intent on sharing data on their BMI, lifestyle, exercise activities, live location, and health records. The decision was made to only ask participants to report on BMI, lifestyle, and health records in the online experiment. The argument for deleting the scenario regarding exercise activities was that not all participants may own smartwatches, so it may be ambiguous for certain individuals to imagine what such data may look like. Second, the argument for erasing the scenario regarding live location is that it may be difficult for some participants to reason why insurers should have access to one’s live location in the first place. Then, the overall language of the survey was simplified to ensure all participants, regardless of their educational level, would be able to apprehend and understand the entirety of the experiment.

3.3.2. Manipulation

The two experimental conditions in this experiment were constructed using the self-determination theory found by Ryan and Deci (1985), as presented in Chapter 2. To ensure participants would be aware of different types of motivation, an introductory text was presented that would prime the reader. To evoke the intrinsic motivator, participants were told that they would be able to help improve the product of the insurer for all users, which likely allows for the emergence of feelings of fulfillment and recognition. Intrinsic motivation is difficult to assess and manipulate (Graef et al., 1983), thus it is crucial to carefully determine how to operationalize it. The key element is to ensure individuals feel valued, as it has been found that praise and recognition increase feelings of intrinsic motivation (Cameron & Pierce, 1994). In the briefing of the experiment, participants were told that being able to help improve the product of the insurer would lead to better health insurance for all customers. These feelings, i.e., recognition and gratification, were planted in the briefing of the experiment to the participants to ensure the link with intrinsic motivation was triggered. To instill the extrinsic motivator in this thesis, participants were told that they would receive a five percent discount on their monthly premium upon the release of their private data. This decision derived from the focus group described prior, in which a threshold was discussed that would act as a motivator while setting a realistic reward. The final decision was made to present the rewards prior to the presentation of the three hypothetical scenarios, as researchers found that the timing of the presentation of rewards can influence motivation. Researchers found that for intrinsic motivation, there was an increased interest, enjoyment, and persistence when receiving a reward immediately or prior to completion (Woolley & Fishbach, 2018). To control for all variables and keep circumstances equal across experimental conditions, both experimental groups were presented with the reward prior to the questionnaire started.

3.3.3. The Experiment

Each participant was required to provide informed consent upon the start of the online experiment. Then, each participant was randomly assigned one of three experimental conditions, each of which informed on the context of the survey. Random assignment is a method to assign individuals to different experimental conditions using an unplanned process, so ultimately groups can be treated as comparable (Neuman, 2014). Additionally, an informational disclaimer was shown to highlight Bland-Acosta's (1988) simplified privacy policy and the General Data Protection Regulation (GDPR) laws in the European Union. The intentional choice to include this disclaimer was made, as people may not know that there are laws in place that ensure data protection. This information may stimulate participants to be more willing to disclose private data knowing that they are protected by law.

Then, participants were asked to answer items relating to behavioral intent, which consisted of the items adapted from Xu et al. (2011). A total of 21 items distributed over three scenarios were asked. After these items, a manipulation check was presented, in which participants were asked to confirm which one of the rewards they would receive upon sharing their private data. More specific to the experimental condition that relates to intrinsic motivation, an additional control question was asked, namely ‘If I can help improve the product of the insurer, so that all users can benefit, would give me a good feeling’. This 7-scaled Likert item, ranging from *strongly disagree* to *strongly agree*, would allow for the control of the participant’s feelings of intrinsic motivation. After the randomization block, all participants were asked to answer the 26 personality questions adopted from John and Srivastava (1999). To finalize the experiment, participants were asked to report on several demographic questions.

3.4. Population, Sampling, and Analysis Procedures

This section will present the sample population and sampling methods used for data collection. Then, the analysis procedures will be described.

3.4.1. The Population

It is unfeasible to accurately compare and generalize international insurance products, hence the decision was made to gather a sample of Dutch citizens to reflect the consumers of insurers. Accounting for just one country, and thus one insurance product, will provide more relevant and reliable findings whilst eliminating possible confounding variables (Scholtens, 2011). In addition to the criterion of being a Dutch citizen, the participant should be at least 18 years of age. The absence of other criteria is done deliberately in an attempt to mimic the breadth of the Dutch society. Having such a varied sample allows insurers to gain insight into their entire customer base, which can be extremely beneficial when marketing to consumers. While experts state $N = 30$ per experimental condition is sufficient (Brysbaert, 2019), after discussing with fellow researchers, the target sample size was increased. The aim was to acquire a sample of $N = 180$, to have each experimental condition hold sixty participants to warrant the validity of the study.

3.4.2. Sampling

Non-probability sampling methods will be employed to obtain data from the population sample. Such methods are distinct for their ease of use and accessibility while having low costs. However, it is important to note that they often lack representativeness and may be associated with personal bias (Levy & Lemeshow, 2013). To warrant a more reliable sample, convenience sampling was carried out beyond the researcher’s personal network. The survey was distributed by six individuals with large networks in different sectors and geographical locations to ensure a varied sample. To illustrate, three individuals are employed in different industries, such as information technology, recruitment, and logistics. The other three reside in different areas, such as the city, a rural area, the countryside. This specific method, a form of snowball sampling, ensures a wider array of respondents and their backgrounds to limit personal bias (Sarstedt et al., 2018). Additionally, the survey was distributed through social networking sites such as LinkedIn and Facebook. The selection of these two sites clarifies the distinction of target audiences, one being more formal and the other more informal, and thus allows for increased control over the sampling process (Bryman, 2016). Lastly, to assure an even more diverse sample, a survey platform, *SurveySwap.io*, was employed to collect more respondents. A financial incentive was offered in an attempt to encourage participation and warrant low dropout rates. Upon completion of the experiment, participants are able to enter the giveaway of a €15,00 gift card. Such incentives have been shown to significantly reduce the dropout rate and can lead to the improvement in completion rates of online surveys by up to 27 percent (Crump et al., 2013; Göritz, 2006).

When posing a sound discussion on sampling methods, transparency is essential. Therefore, possible limitations of non-probability sampling methods should be addressed. Additional to researcher bias, the overall sample may be slightly skewed as participants self-enroll at their own convenience (Horswill & Coster, 2001). In an attempt to limit response bias, the request to complete the survey was drafted to be as neutral as possible. Furthermore, to ensure a valid and reliable sample, attention was paid to multiple submissions. While earlier studies (Reips, 2002) show that multiple submissions are rare, some participants enroll in the study multiple times to increase their odds of obtaining financial compensation. Therefore, multiple submissions were inspected by looking for similar IP addresses and e-mail addresses, and identical addresses were omitted during the data cleaning process. To summarize, when employing non-probability sampling methods, interpreting study results should be exercised with caution (Acharya et al., 2013).

3.4.3. Analysis of the Model

After data collection and data cleaning, the data will be analyzed using the statistics software IBM Statistics SPSS 27. To provide an overview of general findings, such as a sample description and variable descriptives, a short summary is presented prior to conducting analyses. These variables include overall willingness to disclose private data and perceived risk as to the dependent variables, and the personality spectrums and self-determination theory randomizations as the independent variables. Then, normality will be investigated as most analyses require this as an assumption to conduct statistical tests. The last step before hypothesis testing will be the analysis of the control variables, age, and educational level. This will be done using a Pearson correlation coefficient, to explore both the direction and the strength of the relationship between two variables (Pallant, 2016). The first analysis that will be carried out is a confirmatory factor analysis (CFA) using SPSS 27 and AMOS 26. This will provide an indication of the internal consistency of constructs, and the scales will be accepted when coefficients exceed .70 (DeVellis & Thorpe, 2021). To answer Hypothesis 1, an independent-samples t-test will be conducted to explore differences between two experimental groups, with a categorical independent variable and a continuous dependent variable (Pallant, 2016). Furthermore, most data will be obtained on a continuous scale. Therefore, a multiple regression will be conducted to ensure the data remains rich. The interaction effect of the moderator, the reward that is presented based on the self-determination theory, will be calculated and added to the model.

3.5. Validity and Reliability

When conducting quantitative research, especially experiments, there are many threats that may affect the validity and reliability of the study. Therefore, it is vital to discuss such concepts and address limitations.

3.5.1. Validity

Validity is defined as the degree to which a concept is measured correctly (Heale & Twycross, 2015). The aim of conducting a valid study, is to be able to draw valid conclusions about the effects of the independent variables and to generalize findings to a larger population (Malholtra & Birks, 2003). Two principles refer to internal and external validity. To start, internal validity refers to the degree to which a researcher can be certain of a cause-and-effect relationship" (Vargas et al., 2017). To increase the internal validity of the online experiment, manipulation checks are installed throughout the questionnaire. In between questions 17 and 18 of the personality scale, an instructional manipulation check was presented to examine whether participants were carefully reading each item. A second manipulation check was implemented, in which participants were asked to report on the remuneration they were presented within the hypothetical scenarios. Adding these control questions allow, to some extent, for the data to be validated (Abbey & Meloy, 2017). To increase validity further, it is crucial to be transparent about possible threats to internal validity. Face validity describes the accuracy to measure the overall validity of an experimental design (Nevo, 1985). To ensure face validity, a pilot test is conducted that also helps limit construct validity and content validity, as fellow researchers and potential participants were asked to provide feedback on the questionnaire. Receiving feedback from professionals and members of the population sample helps figure out whether question items should be revised. These two measures of validity are crucial to discuss, as they describe whether the test measures the concept that it is intended to measure and whether it is fully representative (Nevo, 1985).

Furthermore, Neuman (2014) presents multiple potential threats in his earlier studies. To start, *selection bias* was limited by employing random assignment to each experimental group through the randomization tool in Qualtrics. As the online experiment is a true experimental that only took participants about ten minutes to complete, no *maturation effects* were probable as they are more common in longitudinal studies. Additionally, *testing effects* likely did not occur as respondents who partook in the experiment did not partake in the pre or post-test. The validity was likely not harmed with regard to *instrumentation*, as the experiment was entirely automated, thus changes in instrument calibration do not apply. Lastly, *experimental mortality* was reduced as participants who failed to complete the entirety of the survey were omitted during the data cleaning process. Addressing these potential threats identified by Neuman (2014) allowed for a transparent dialogue concerning validity.

External validity refers to the capability of the researcher to generalize findings from one study to other settings (Vargas et al., 2017). In this study, ecological validity contributes to the external validity, as elements of experiments are consistent with aspects that people encounter in everyday life (Burgess et al., 1998). Since the experiment was conducted digitally, it resembles a real-life setting more than a controlled environment, thus more confidence can be given to the generalizability of findings (Dandurand et al., 2008). Though this experiment is conducted digitally, without the presence of a researcher, and completely anonymous, feelings of 'being observed' may occur, thus creating a Hawthorne effect. An individual's behavior may have changed as they were aware of partaking in research, thus making it more difficult to generalize results beyond this study (Adair, 1984). A second concept that relates to external validity is population validity, which deals with generalizations to populations, that is whether the population is likely to act similarly to the subjects in the sample (Bracht & Glass, 1968). Being able to generalize the findings of this thesis to a wider population is crucial, as it makes a study more relevant. Therefore, it is important to gain a sample reflective of the actual population. This is ensured through a carefully thought out sampling method, though it has to be taken into consideration that non-random sampling methods are employed, making it less likely to generalize findings beyond this study (Bracht & Glass, 1968).

3.5.2. Reliability

Reliability is defined as the accuracy of a study and the consistency of the scales used in the research (Heale & Twycross, 2015). Internal consistency, or homogeneity, is assessed using Cronbach's α. If the Cronbach's α results are above .70, there is sufficient evidence that the items are reliable (Saunders et al., 2016). The online experiment consisted of items derived from validated scales. The behavioral intent scale by Xu et al. (2011) was validated within their study as the loading of each item exceeded the criterion of .70. Likewise, the Big Five Personality Index is the most scientifically validated and reliable psychological model to measure personality traits common to all human groups to date

(McCrae & Terracciano, 2005). Both of these scales are used to reverse items to force participants to carefully read and process each item thoroughly in an effort to avoid response sets (Weems et al., 2003).

It is important to note that while these scales are carefully translated from English to Dutch, some threats to the reliability of the scales may arise. To statistically vouch for the reliability of this study, the Cronbach's α will be investigated for the translated items. To further ensure reliability, the experimental method is identical for each participant in each experimental condition. Using a digitalized experiment results in a more reliable study, as all internal conditions, such as use of language and the amount of information provided, are held to a constant.

In this chapter, the conceptual model was operationalized and the methodology for this study was discussed. In the following chapter, results that are derived from the conceptual model will be presented.

4. Results

In this chapter, the twelve hypotheses will be tested using quantitative analysis techniques. To start, a sample description will be provided, then a general overview of variable descriptives are shown, followed by measures of reliability. Then, each hypothesis will be tested and its results will be presented.

4.1. Sample Description

A total of 268 responses were recorded from April 26th through May 5th, 2022. Upon cleaning the raw data, it was found that six participants did not complete the survey. The completion rates for these participants lie between 34 and 57 percent. The decision was made to delete these incomplete responses. No multiple submissions were detected, which aligns with the predictions of Reips (2002). In total, nine participants failed to answer the manipulation checks accurately. Therefore, the final sample was lowered to N = 253.

The sample consisted of 66.80% female respondents, (*N* = 169), 31.2% male respondents (*N* = 169), while .8% of participants identified as non-binary (*N* = 2), and 1.2% of participants preferred to omit information on their gender (*N* = 3). The participants' ages ranged from 18 to 86 years old. A table with the categorization of participants' ages is presented in Table 3.

Table 4.1

Sample description for age (N = 253)

	Age	N	Percentage
	18-22	42	16.6
	23-26	53	20.9
	27-32	20	7.9
	33-45	43	17.0
	46-56	54	21.3
	56-86	41	16.2
Total		253	100.0

As for educational level, participants were asked to report on their highest obtained diploma or to report on which diploma they are currently obtaining. A high school diploma is the highest level of education for 11.1% of this sample (*N* = 28). A vocational diploma is the highest level of education for 10.7% of this sample (*N* = 27). Next, 10.7% have obtained a Bachelor's degree (*N* = 159), followed by 15% have obtained a graduate/post-graduate degree (*N* = 38). Regarding regional area, 29.6% of participants reported that they live in a large city (*N* = 75), 45.1% reported that they live in a town (*N* = 114), 22.90% reported that they live in a village (*N* = 58), and 2.4% reported that they live in a rural area (*N* = 6).

When participants were asked to report information on their technology use and views on data sharing, their answers were as follows: When asked if they owned a smartwatch (e.g., Apple Watch, Samsung Watch, FitBit), 36.7% reported that they did own a smartwatch (*N* = 93), and 63.20% reported that they did not own a smartwatch (*N* = 160). The next item asked whether participants were knowingly sharing data at the moment, 45.5% said they did knowingly share data *(N* = 115), while 54.5% reported that they were not knowingly sharing data at the moment (*N*=138). Then, participants were informed about how many data points Facebook roughly has on each user (Isaak & Hanna, 2018). Lastly, when asked to report if they were aware of how much data was being collected, 69.6% of participants reported that they were aware (*N* = 176), while 30.4% stated they were not aware of how much data are being collected *(N* = 77).

4.2. General results

To provide a summary of general results before testing the hypotheses, more general variable descriptives will be provided. In-depth descriptives and thorough analyses will be presented further in this chapter, this section merely serves to provide a bird's-eye view of the most important variables in the conceptual model. As for the randomization aspect of this experiment, an equal distribution setting was applied in Qualtrics to ensure proportionate dispersion of participants across experimental conditions. However, these three groups held different numbers due to termination during the data cleaning process. General findings of each experimental condition along with results from the dependent variable are presented in Table 4.2. When looking at the mean scores of all three experimental conditions, participants reported that their overall willingness to disclose private data is *M* = 3.45, *SD* = 1.53. In this table, it can be seen that simply comparing means, the control group shows the lowest willingness to disclose their private data, while the intrinsic experimental group, on average, has the highest willingness to disclose. As for perceived risks, the descriptives for all three groups combined were *M* = 4.52, *SD* = 1.40. It shows the intrinsic group scored the lowest on perceived risk, while the extrinsic group scored the highest on this variable

Table 4.2

General findings experimental conditions

	M	*SD*	*N*	Percentage
Extrinsic experimental condition			89	35.2
Overall willingness	3.38	1.59		
Perceived risk	4.76	1.37		
Intrinsic experimental condition			77	30.4
Overall willingness	3.80	1.40		
Perceived risk	4.09	1.33		
Control group			87	34.4
Overall willingness	3.18	1.56		
Perceived risk	4.65	1.41		

4.3. Preparation for hypothesis testing

Prior to answering the drafted hypotheses, multiple steps were taken in preparation. Items were reversed, namely BI3 for the behavioral intent scale, and PA1, PA3, PA6, PA8, PC2, PC4, PC5, PC8, PN2, PN5, and PN7 for the personality scale to follow the procedure of the pre-existing scales. Then, prior to computing new variables, reliability tests and a factor analysis is conducted.

4.3.1. Normality

Upon preparation for hypothesis testing, multiple aspects need to be inspected. To start, the normality was reviewed. The skewness and kurtosis values were converted to a z-score where:

$$Z_{Skewness} = \frac{Skewness - 0}{SE_{Skewness}} \quad \text{and} \quad Z_{Kurtosis} = \frac{Kurtosis - 0}{SE_{Kurtosis}}$$

The variables in the conceptual model that exceeded < -2.58 or > 2.58 are neuroticism, intrinsic rewards, intrinsic risks, extrinsic rewards, extrinsic risks, control rewards, and control risks are insignificant, and thus normally distributed by standards provided by Ghasemi and Zahediasl (2012). On the other hand, variables agreeableness ($Z_{Skewness}$ = -5.22), conscientiousness ($Z_{Kurtosis}$ = -8.30), educational level ($Z_{Skewness}$ = -5.75), age ($Z_{Skewness}$ = 2.92 and $Z_{Kurtosis}$ = -2.93), and residential area ($Z_{Kurtosis}$ = -3.63), are not normally distributed as they are significant at p < .001. While experts state that the violation of normality assumption in larger sample sizes should not cause major problems, and parametric procedures can be used (Ghasemi & Zahediasl, 2012), it is important to keep in mind that the majority of the variables used in this research are in fact not normally distributed. In addition to calculating z-scores, visual inspection was employed to review the normality of the variables. To start, both behavioral intent variables showed a bell-curved slope, though willingness to disclose is negatively skewed, and perceived risk is positively skewed. While agreeableness and conscientiousness showed a positively skewed bell-curved slope, neuroticism showed a centered, bimodal distribution. Next, age shows a bimodal distribution, with a high left-skewed peak. Lastly, educational level shows a bell-curved slope that is slightly positively skewed.

4.3.2. Control variables

As discussed in Chapter 3, any experimental design relies heavily on control variables. The use of such variables is needed to rule out threats to internal validity by avoiding Type I errors (Nielsen & Raswant, 2018). In this research design, age and educational level were used as possible confounding variables. To test for the covariance of these two variables, a Pearson correlation coefficient was employed. To start, age showed to have a significant association with the willingness to disclose data, with r (253) = -.22, p <.001. Thus, age indicates a significant negative relationship with the willingness to disclose data. For the second dependent variable used in this study, perceived risk, a second Pearson

Correlation was employed. This showed that age holds a significant association with perceived risk, *r* (253) = .14, p = .022. Therefore, age indicates a significant positive relationship with perceived risk. Accordingly, age is included as a covariate for further statistical analyses.

To test the second control variable, educational level, a third Pearson correlation coefficient was measured. This coefficient shows that there is no significant association between the educational level and willingness to disclose *r* (251) = .03, p = .695, nor with perceived risk *r* (251) = .04, p = .552. These results demonstrate that including educational level as a covariate is not necessary.

4.3.3. Factor analysis

While the pre-existing personality scale was adopted from John and Srivastava (1994), a confirmatory factor analysis (CFA) was conducted to ensure the reliability of the scale. CFA is a sophisticated technique to identify and confirm theories regarding an underlying set of variables (Pallant, 2016). Prior to conducting factor analysis, assumptions of the analysis provided by Pallant (2016) and Alhija (2010) were inspected. To start, the sample should exceed 150 participants, which this sample surpasses (N = 253). Furthermore, *a priori* criteria were checked, and it was found that the linearity between variables was quite low. However, as Pallant (2016) suggests, it is safe to proceed with the CFA even with modest relationships. Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) measures were explored, and as both values were adequate, (p <.001) for the Bartlett's test and the KMO-index is .79, the confirmatory factor analysis proceeds.

Using AMOS 26, it was found that the measures of overall fit did not meet the conventional standards of modelling, as χ^2 (132) = 321.89 , RMSEA = .08, CFI = .85, and TLI = .82. The model is presented in Appendix D, along with the model fit summary. With that being said, regular confirmatory factor analysis revealed that the scales did not accurately convert to the context of this experiment. When investigating the pattern matrix in SPSS, the analysis identified multiple items under different factors than the verified scale by John and Srivastava (1994) shows. For instance, the analysis identified items PA5 and PA9 under the neuroticism component, while PC3 fell under the agreeableness component. Additionally, seven items had loadings below .50, and per Matsuaga's (2010) prior research, this can be used as a cutoff value for social scientific studies as an acceptable threshold. For agreeableness, PA1 (loading = -.33), PA3 (loading = -.44), PA5 (loading = -.47), and PA9 (loading = -.35) were disregarded from the component. For conscientiousness, PC1 (loading = -.44), and PC3 (loading = .38) were disregarded. For neuroticism, only PN6 (loading = .35) was disregarded. A second confirmatory factor analysis was conducted to assure appropriate values. The deletion of the items meant an increase of the Cronbach's α, as these all show acceptable values that exceed .70. Findings are presented in Table 4.3.

Table 4.3

Factor and reliability analyses for scales of personalities

Item	*Neuroticism*	*Conscientiousness*	*Agreeableness*
Gets nervous easily	.82		
Is relaxed, handles stress well	.78		
Is emotionally stable, not easily upset	.77		
Worries a lot	.75		
Can be tense	.71		
Remains calm in tense situations	.68		
Is depressed, blue	.51		
Tends to be disorganized		.77	
Tends to be lazy		.68	
Makes plans and follows through with them		.68	
Is easily distracted		.68	
Perseveres until the task is finished		.57	
Can be somewhat careless		.55	
Is considerate and kind to almost everyone			.80
Is sometimes rude to others			.63
Is helpful and unselfish with others			.63
Has a forgiving nature			.56
Can be cold and aloof			.53
R^2	.21	.15	.10
Cronbach's α	.85	.74	.70

Prior research by Fletcher et al. (2000) was followed to compute summated scales after the confirmatory factor analysis. Descriptives for the newly computed variables can be found in Table 4.4. These variables are measured on a 7-point Likert scale, thus agreeableness and conscientiousness show a positively skewed distribution.

Table 4.4

Descriptive data for personality scales (N = 253)

	Agreeableness	Conscientiousness	Neuroticism
Mean	5.42	5.20	3.50
Median	5.56	5.25	3.50
Std. Deviation	.67	.78	.97
Minimum	3.11	2.75	1.00
Maximum	7.00	6.88	6.00

The dependent variable in this research design is constructed as behavioral intent, which is assembled from the three experimental conditions. When looking at the behavioral intent scale by Xu et al. (2011), the internal consistency of all nine scenarios was measured by inspecting the Cronbach's α for both the willingness to disclose data and for perceived risks. For the willingness to disclose data, findings showed that item BIW3, a reversed item, caused a lower Cronbach's α for each variable. Suárez Álvarez et al. (2018) discuss the possible harms of reversed items, as they present a trade-off between potential acquiescence bias and potential different understandings when combining regular and reversed items within the same test. With that being said, the item was deleted which caused all nine variables, three scenarios in each of the three experimental conditions, to have a Cronbach's α of >.93.

These nine variables all had Pearson correlation coefficients that exceeded *r* (251) = .72, *p* <.001 (2-tailed) in relation to the variable of overall willingness. As for perceived risks, all items were sustained and each showed Cronbach's α of >.70, with Pearson correlation coefficients that exceeded *r* (251) = .71, *p* <.001 (2-tailed). Based on the newly computed variables, descriptives of experimental conditions compared to the most prominent dependent variable in this research design are presented in Table 4.5. This table shows that the relative means of the willingness to disclose data decreased slightly per scenario in the control and extrinsic condition, while the mean increased slightly in Scenario 2, and then decreased drastically for the intrinsic condition.

Table 4.5

Willingness to disclose data based on experimental conditions and each scenario

	Control (N = 87)		*Extrinsic (N = 89)*		*Intrinsic (N=77)*	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
BMI data (S1)	3.29	1.74	3.73	1.84	4.05	1.65
Lifestyle data (S2)	3.14	1.73	3.42	1.79	4.20	1.68
Health data (S3)	3.10	1.76	3.00	1.72	2.15	1.55

4.4. Hypothesis testing

To be able to answer the proposed research question, the hypotheses will be presented along with the appropriate statistical analyses and their results.

***H1** Participants will be more willing to disclose private data when receiving an extrinsic reward compared to participants who are presented with an intrinsic trigger*

An independent-samples t-test was conducted to compare the willingness to disclose data for participants who received either the extrinsic reward or the intrinsic trigger. Assumptions for this analysis require the dependent variable to be measured as a continuous scale, which the willingness to disclose private data is (Pallant, 2016). Additionally, assumptions regarding random sampling and independence of observations are both appropriate. As mentioned in Chapter 4.3.1., normality is violated in the variables used for this analysis, though in larger sample sizes this should not cause major problems (Ghasemi & Zahediasl, 2012). Lastly, to test homogeneity of variance, a Levene's test for equality of variances is employed, which found (F = 1.44, *p* = .065), thus equal variances are detected. With that being said, the independent-samples t-test was conducted, and found that there was no significant difference in scores for the extrinsic reward (*M* = 3.38, *SD* = 1.59) and intrinsic reward (*M* = 3.83, *SD* = 1.36); *t* = (164) = -1.93, *p* = .06, two-tailed. The magnitude of the differences in means (mean difference = .-.45, 95% *CI*: -9.04 to .01) lies between a small and medium effect for group comparisons (Cohen's *d* = 0.30), where Cohen (1992) suggests:

$$\text{Cohen's } d = (M_2 - M_1) / SD_{\text{pooled}}$$
$$SD_{\text{pooled}} = \sqrt{((SD_1^2 + SD_2^2) / 2)}$$

This means that there is a probability of .94 of obtaining a difference between the two groups. As the significance level was set at <.05, H1 is rejected as one fails to reject the null hypothesis, therefore, no statistical conclusion can be drawn that participants who receive an extrinsic reward are not more willing to disclose private data compared to those who are presented with an intrinsic trigger.

When moving on to the next hypotheses, it is important to see whether the variables are correlated. To do so, Pearson Correlation Coefficients were calculated and presented in Table 4.6.

Table 4.6

Pearson Correlations of agreeableness, conscientiousness, neuroticism, and the willingness to disclose

Variable	1	2	3	4
1. Agreeableness	-			
2. Conscientiousness	.22**	-		
3. Neuroticism	-.10	-.14*	-	
4. Willingness to disclose	.09	.07	-0.35	-

Note *. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

Then, to carry out further analyses, a multiple regression analysis was conducted to estimate the relationship between continuous variables. This analysis seeks patterns within the model, so that predictions on the dependent variable can be made (Pallant, 2016). The first of multiple assumptions for this statistical analysis that needs to be met is an appropriate sample size, which the sample size of this study abides by when $N = 253$. Second, no extreme outliers were identified through a standardized residual plot. The scatterplot showed only a few outlying residuals, though this is not uncommon in a larger data set, thus this assumption is supported. Next, linearity was investigated and while this relationship should ultimately result in a straight line with the predicted dependent variable, one actually sees a weak relationship between the variables. Then, multicollinearity is explored prior to conducting the analysis, which refers to the fact whether independent variables are, in fact, independent. When collinearity tolerance is checked, variables did not exceed the threshold as suggested by Weisburd and Britt (2014), who state that values below .20 suggest serious multicollinearity. As discussed in Chapter 4.3.1., normality is violated in some variables entered in this research, though due to a larger sample size, the analysis proceeds. The willingness to disclose private data was used as a dependent variable, while multiple independent variables were entered to assess relationships. The randomization, based on the extrinsic and intrinsic motivator, was transformed into a dummy variable, meaning that both of the two experimental conditions are being compared to the control group. These dummy variables, along with the three personalities and the interaction effects, which were computed with Z scores, were entered as independent variables. Lastly, the covariate that was established in Chapter 4.3.2., namely age, was added to the model as well. The overall model with twelve variables did reach significance, as $R^2 = .10$, F (12,

240) = 2.23, *p* = .011. This, therefore, refers to the predictive ability of the set of independent variables on the dependent measure (Pallant, 2016). The R^2 in the overall model shows how accurately the regression model explains the observed data, meaning that .10 of the variance observed is explained by the model. In this model, standardized coefficient beta's are used to pinpoint the smaller effect size of variables and more useful for direct comparison when measurement scales of independent variables are different (Pallant, 2016). The overall model is presented in Table 4.7.

Table 4.7

Multiple Regression with the willingness to disclose as a dependent variable

Model	*R*	*R Square*	*Adjusted R Square*	*F Change*	*DF1*	*DF2*	*Sig. F Change*
1	.317	.100	.055	2.230	12	240	.011

Model		*Sum of Squares*	*DF*	*Mean Square*	*F*	*Sig.*
1	Regression	59.180	12	4.93	2.230	.011
	Residual	530.67	240	2.21		
	Total	589.85	252			

Model		*Pearson Correlation*	*Standardized Coefficients Beta*	*t*	*Collinearity Tolerance*
1	(Constant)	.	.	13.986**	.
	(Dummy) Extrinsic	-0.31	.044	.619	.754
	(Dummy) Intrinsic	.166**	.179	2.534*	.752
	Agreeableness	.086	.057	.560	.367
	Conscientiousness	.074	.164	1.522	.322
	Neuroticism	-.035	-.029	.028	.356
	Interaction Ex*Agree	.046	.050	.605	.550
	Interaction Ex*Con	.006	-.118	-1.288	.445
	Interaction Ex*Neuro	-.042	-.064	-.741	.502
	Interaction In*Agree	.016	-.009	-.112	.528
	Interaction In*Con	.026	-.052	-.627	.549
	Interaction In*Neuro	.007	.007	.085	.547
	Age	-.210**	-.243	-.3.781**	.904

Note *. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

The multiple regression model will be used to report on the following hypotheses.

H2a *There is a positive effect between agreeableness and willingness to disclose private data*

When exploring the effect on agreeableness (*M* = 5.37, *SD* = .82) to willingness to disclose data, it is found that there is an insignificant positive effect (β = .06, *p* = .576). This means that there is a likelihood of .42 that the model can predict that agreeableness affects the willingness to disclose, while that percentage should be .95. Therefore, H2a is rejected, as one fails to reject the null hypothesis.

H2b *The effect of agreeableness on willingness to disclose private data is moderated by a reward*

When looking at the randomization of the reward as a moderating variable, the interaction between the reward and agreeableness was explored. Both the extrinsic reward (β = .05, *p* = .546) and the intrinsic reward (β = -.01, *p* = .911) did not yield significant results. With these findings, H2b is rejected, as one fails to reject the null hypothesis.

H3a *There is a positive effect between conscientiousness and willingness to disclose private data*

When exploring the effect on conscientiousness (*M* = 4.94, *SD* = .94) and willingness to disclose data, it is found that there is an insignificant positive effect (β = .16, *p* = .129). These findings infer that there is a likelihood of .87 that the model can accurately predict that conscientiousness affects one's willingness to disclose private data. With that being said, H3a is rejected, as one fails to reject the null hypothesis.

H3b *The effect of conscientiousness on willingness to disclose private data is moderated by a reward*

When looking at the randomization of the reward as a moderating variable, the interaction between the reward and conscientiousness was explored. Both the extrinsic reward (β = -.12, *p* = .199) and the intrinsic reward (β = -.05, *p* = .532) did not yield significant results. With these findings, H3b is rejected, as one fails to reject the null hypothesis.

H4a *There is a positive effect between neuroticism and willingness to disclose private data*

When exploring the effect on neuroticism (*M* = 3.42, *SD* = 1.03) to the willingness to disclose data, it is found that there is an insignificant positive effect (β = -.03, *p* = .781). With these results, it states that there is a likelihood of .22 that the model can accurately predict the effect neuroticism has on the willingness to disclose their private data. Therefore, H4a is rejected, as one fails to reject the null hypothesis.

H4b *The effect of conscientiousness on willingness to disclose private data is moderated by a reward*

When looking at the randomization of the reward as a moderating variable, the interaction between the reward and neuroticism was explored. Both the extrinsic reward (β = -.06, *p* = .460) and the intrinsic reward (β = .01, *p* = .932) did not yield significant results. With these findings, H4b is rejected, as one fails to reject the null hypothesis.

Moving to the next set of hypotheses, H5 is the first to use perceived risk as a dependent variable. It aims to investigate the relationship between conscientiousness and perceived risk, and it will employ a simple regression to find possible explanations between two continuous variables. Assumptions described by Pallant (2016) state that linearity should be ensured, which was inspected through a P-Plot, which showed a linear line. Then, the independence of errors showed a low correlation, which implies that there is no relationship. Lastly, as described in the earlier section on normality, variables did not abide by appropriate statistics, although the chart did display a bell-curve normal distribution. Therefore, the analysis complies with the assumptions, thus the parametric analysis is conducted.

H5 *There is a positive effect between conscientiousness and acknowledging potential risks of data sharing*

The simple regression was conducted to explore the relationship between conscientiousness and the acknowledgment of potential risks of data sharing. The overall model did not reach significance, with $R^2 = .09$, $F(1, 251) = 2.20$, $p = .139$. Therefore, H5 is rejected, as one fails to reject the null hypothesis.

For the last set of hypotheses, one-way between-subjects ANOVA's will be conducted to compare the effects of the variables age and educational level on behavioral intent. Prior to completing these analyses, assumptions were checked to ensure this parametric test would be appropriate. To start, and this refers to all hypotheses, normality is violated as discussed in an earlier section. With that being said, a one-way ANOVA is considered to be fairly robust, thus non-normal variables can be used as long as there is an appropriate sample size. The assumption of independence asks that participants were obtained through a random sample. The participants were divided randomly through random assignment. Each individual Levene's test for equality will be provided per individual hypotheses.

H6a *There is a positive effect between age and willingness to disclose private data*

A one-way between-subjects ANOVA was conducted to compare the effect of age on willingness to disclose data. Levene's test for equality of variances is employed, which found ($F = .66$, $p = .578$), thus equal variances are detected. Therefore, the analysis proceeds. There was a significant effect of age on willingness to disclose data at the $p < .05$ level as $F(5, 247) = 3.58$, $p = .004$. Tukey's post hoc comparison revealed that participants between the aged 18 to 22 showed significant higher willingness to disclose data ($M = 4.07$, $SD = 1.34$) than participants aged 46 to 56 ($M = 3.00$, $SD = 1.40$), $p = .008$. Additionally, the same post hoc comparison revealed that participants between the ages of 23 to 26 showed significant higher willingness to disclose data ($M = 3.88$, $SD = 1.50$) than participants aged 46 to 56 ($M = 3.00$, $SD = 1.40$), $p = .048$. No other comparisons reached significance. The overall ANOVA model with post hoc comparisons is presented in Appendix E.

H6b *There is a positive effect between age and perceived risk to share private data*

Levene's test for equality being ($F = 1.94$, $p = .124$), thus one-way between-subjects proceeds. The ANOVA explored the relationship between age and perceived risk. The overall model did not yield significant results, at the $p <.05$ level as $F(5, 247) = 1.89$, $p = .097$.

When looking at the relationships between either the willingness to disclose private data and perceived risks of sharing private data with educational level, it was hypothesized that there would be positive relationships between these variables. To conduct this analysis, one participant, who preferred not to answer the question on their educational level, was deleted in this specific analysis as post hoc tests would not be able to be conducted as one group had fewer than two cases.

H7a *There is a positive effect between educational level and willingness to disclose private data*

While it appears that participants who have obtained higher levels of education are comparatively higher when simply comparing means, it is important to further investigate whether these first-glance differences are statistically significant. The educational groups were entered as the independent variable, and the perceived risks as the dependent variable. The fourth assumption, namely Levene’s test for equality was investigated, which was (F = .66, *p* = .578), thus the ANOVA proceeds. The ANOVA did not reveal a significant main effect for educational level on the willingness to s disclose private data, as *F* (3, 248) = .29, *p* = .834. Therefore, no statistical conclusions can be drawn on whether there is a positive effect between educational level and the willingness to disclose private data. With that being said, H7a is rejected, as one fails to reject the null hypothesis.

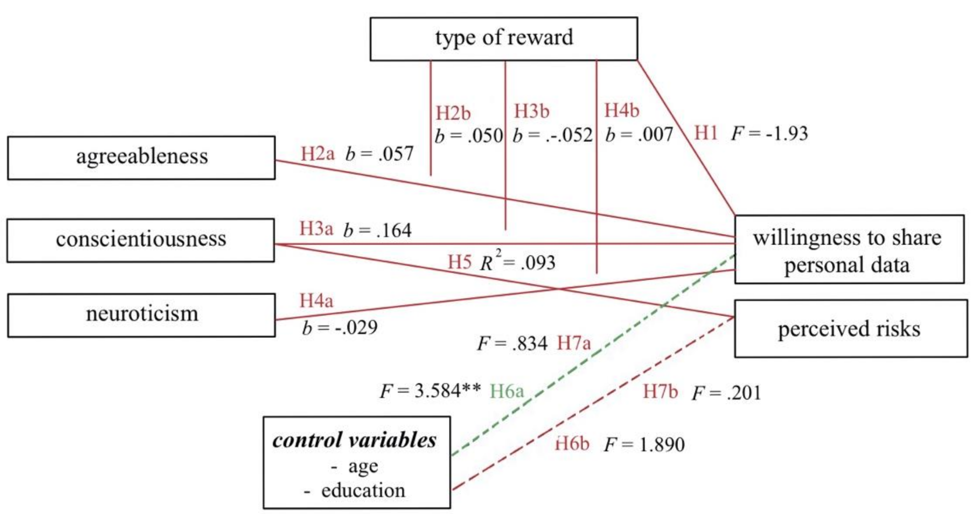
H7b *There is a positive effect between educational level and perceived risks of data sharing*

For the final hypothesis, identical assumptions were checked and the Levene’s test for equality was investigated (F = 1.40, *p* = .224). These statistics abide by the assumption, and thus the analysis proceeds. Similar to the prior hypotheses, a one-way between-subjects ANOVA would reveal any possible effects between educational level and perceived risk. The analysis did not reveal a significant effect of educational level on perceived risk, as *F* (3, 248) = .20, *p* = .895. Therefore, H7b is rejected as one fails to reject the null hypothesis.

A visual representation of results is presented in Figure 2. To summarize, the only hypothesis that reached significance is H6a. This infers that all other hypotheses are rejected, and no statistically sound conclusions can be drawn. Possible explanations and implications will be presented in Chapter 5.

Figure 2

Summary of findings



**. Correlation is significant at the 0.01 level (2-tailed).

5. Conclusion and discussion

In this final chapter, the results of the experiment will be interpreted and discussed to help guide the answering of the proposed research question. Implications will be presented with regard to theoretical, managerial, and societal inferences. This section is followed by limitations, and then by suggestions for further research. Lastly, a short conclusion will be provided that will conclude this thesis.

The aim of this research is to examine the influence of the self-determination theory on psychometrics and the willingness to disclose private data. The concept of understanding the phenomenon of data sharing is becoming exceedingly important as the value of data is exponentially rising (Forbes, 2019; Deloitte, 2015). The scarcity of literature on the utilization of personality marketing in the insurance sector induced the empirical exploration of this notion using an online experiment, intending to expand both theoretical and practical concepts.

5.1. Key findings

While it is certainly preferable that hypotheses reach significance to be able to conclude statistical differences between variables and ultimately, models, it is still fair that few significant findings have been detected. To start, the multiple regression model reached significance, meaning that there is a significant probability this model can accurately predict one's willingness to disclose private data. However, the proportion of variance in the model is quite low, although Frost (2020) states that most studies that foresee human behavior tend to have lower R^2 values as humans are inherently more difficult to predict. This is due to the fact that human behavior depends on many extraneous variables that easily change, such as one's mood, how someone interprets questions regarding mood, or how they interpret scale points. Extraneous variables will be discussed more thoroughly in Chapter 5.4.

A second result that was not necessarily hypothesized, but discovered by the multiple regression, is the comparison between the intrinsic experimental condition with the control group. A significant result showed that participants who received an intrinsic reward, also referred to as an intrinsic trigger, were more willing to share private data compared to participants who did not receive a reward at all. The first experiment to test the effects of intrinsic reinforcement on motivation was conducted by Deci (1971), who found groundbreaking evidence for the effects of motivation on a control group. These findings are further substantiated by the theory of Cameron and Pierce (1994) who supported Deci's initial findings.

Other findings that reached significance mainly were related to age, which does not necessarily pertain to the main variables of psychometrics in this research. Although it is important to note that every significant finding is a valuable observation. The final significant finding was the relationship between age and the willingness to disclose data. Tukey's post hoc comparisons revealed that there was a significant difference between participants between the ages of 18 to 22 and those between the ages of 46 to 56. Additionally, there was a significant difference between participants between the ages of 23 to 26 and participants between the ages of 46 to 56. Thus, while no variables regarding personalities reached significance in this study, age is, in fact, a significant predictor of the willingness to disclose private data. Additionally, a simple Pearson correlation coefficient revealed a significant relationship between age and both behavioral intent variable, with willingness to disclose data being a negative relationship, and perceived risk being a positive relationship.

While no other hypotheses identified significant findings, it is established that no other statistically sound conclusions can be drawn from the obtained data. After looking at the correlations presented in Table 4.6, it was expected that most hypotheses would not reach significance as merely weak relationships were found. Beyond these findings, however, it was interesting to simply compare means of outcome variables, as it was found that participants, across all three experimental conditions, were least likely to share their health data (e.g., blood reports) compared to their BMI or lifestyle data. Most surprisingly, no direct effect was found between psychometrics and behavioral intent. Possible explanations for the weak relationships between variables and the insignificance of the hypotheses will be discussed in Chapter 5.2.

In the first chapter of this thesis, a research question was proposed that would guide this study. After having investigated the extent of the self-determination theory on the relationship between personality dimensions and the willingness to disclose private data to the insurance sector in the Netherlands, no significant relationships have been found that substantiate the evidence to answer this research question. However, strong assumptions remain that relationships between the conceptual model exist, even though this study was not able to identify them. Possibly, through different methods of testing or making adjustments to the research design, these relationships can be uncovered. Suggestions for further research are discussed later in this chapter.

5.2. Implications

Making implications is vital in any empirical study, as it helps convey why these concepts are important to both practice and theory. In this section, theoretical, managerial, and societal implications will be voiced to reiterate the importance of this research and what its results mean for academia, organizations, and society.

5.2.1. Theoretical implications

The main effect of this study, namely the effect of psychometrics on the willingness to disclose private data, did not reveal significant findings. This contradicts existing literature, as experts have found promising results with regard to this marketing approach (Hirsh et al., 2012; Matz et al., 2017; Winter et al., 2021). These results shed light on the relationship between personality traits and marketing outcomes, such as conversion rates and product favoritism. When inquiring for possible explanations, it can be implied that the discrepancy between a consumer setting and a hypothetical scenario for an insurance sector is what may have caused results to not transfer to this research design. It can, therefore, be inferred that there is too little transmission between different experimental settings, namely between the consumption of physical products and an intangible contract, such as health insurance.

Additionally, it was surprising that no significant relationships between the extrinsic experimental group and the control group were discovered. Existing literature has repeatedly found that individuals are more likely to be motivated by extrinsic behavior compared to intrinsic behavior, especially compared to a control group (Deci, 1971; Killeen, 1982). Therefore, it was unforeseen that these variables did not yield significant results. A possible explanation for this result can be traced back to the sampling method for this research. Non-randomized sampling methods were employed to collect data, and potential recruits were contacted with a, inherently intrinsically motivated, message. Namely, it was explained that participants could help the researcher with their Master's thesis, which in turn can increase intrinsic motivation. In an attempt to counter this inclination, an extrinsic reward was presented. Potential recruits were told that they could enter a contest to win an electronic gift card upon completion of the experiment. While individuals are heterogeneously motivated, meaning that they hold different values and are motivated through different notions (Hiesh & Kocielnik, 2016), it may have been possible that more intrinsically motivated individuals felt more inclined to partake in the research based on the strength of the intrinsic trigger (Cameron & Pierce, 1994). This prevalent phenomenon relates to participant bias, and may have led findings to contradict prior literature (Brito, 2017).

Besides the main effect not reaching significance, the interaction effects in this study did not reach significance either. It was hypothesized that the joint effect of two variables, namely psychometrics and motivation, are significantly greater than the sum of their parts (Lavrakas, 2008). Unexpectedly, all three interaction effects tested did not reach significance.

However, ultimately, not finding statistical evidence to the drafted hypotheses in itself provides meaningful insight into the scope of personality. Namely, it can be justified that there is no simple explanation behind the motivational drivers of individuals to share their private data. It is not just those who score high on agreeableness, or those who score low on neuroticism. Not having the answer to what drives behavioral intent is a testament to the complexity of this notion, thus it is crucial this concept should be investigated further before implementing personality marketing strategies in business imperatives.

5.2.2. Managerial implications

While most of the significant results are not derived from psychometrics, it is important to note that findings that do not align with the hypothesized results still hold value. Though the argument for implementing personality marketing was not supported statistically, findings do show that personalized marketing, a less niche, more overarching approach, is still a valuable marketing strategy. As it was found that individuals in certain age groups are not just more willing to disclose their private data, but some are also less likely to acknowledge the perceived risks of this process. With this information, it is proven that targeted marketing works, also in the market segment of insurance. While segmenting customers based on age does not involve psychometrics, it is still a way to personalize communications to certain target groups. This holds managerial value, as insurers can alter their marketing strategies to use this approach to help reach marketing goals more efficiently.

As mentioned prior, it is crucial that there is academic evidence of implementing personality marketing in the market segment of insurance. To reiterate, it is crucial that more research should be conducted to help organizations understand the intricate concept of personality marketing that appears to have numerous complex layers. Implementing such strategies prematurely involves risk as it can seriously harm an organization's image and reputation. Especially in the market of insurance, it is crucial to ensure customers' trust and be deemed as an honorable and ethical organization.

5.2.3. Societal implications

Datafication and digitalization will only progress as time goes by (Clark & Calli, 2014). Therefore, it becomes increasingly important that society becomes aware of the conveniences, and more importantly, possible risks of these technological advancements. This research showed that the majority of participants were not aware of the amount of data they were sharing, and roughly a third of the sample was not aware of the fact that they were sharing data at all. Data sharing is an abstract concept that not many people unequivocally understand. With that being said, governmental and/or non-profit organizations should realize that most members of society are uneducated on this specific topic, and offer ways to relieve this lack of knowledge. Statistics from this research showed that overall, willingness to disclose data was comparatively lower than their perceived risk. This may imply that there is generally a lack of trust in privacy with regard to private data sharing. Even with the GDPR that was passed by the European Parliament in 2016, many individuals may not be aware of these laws or know what exactly they entail. Again, a societal implication is that consumers' privacy should be highlighted through campaigns, so members of society can become more aware of their rights with regard to private data. The Cambridge Analytica case has shown what harm personality marketing can do when it falls into the wrong hands and thus it is crucial to prevent misuse of these approaches. This lies with each user of social media platforms, but also with governments that need to ensure the protection of individuals. In the future, strategies such as personality marketing can only occur ethically if all parties involved, meaning both organizations and society as a whole, are aware of both possible risks and benefits.

5.3. Limitations

While the outcome of this study can infer that psychometrics simply do not play a role in one's behavioral intent to share private data in the market segment of insurances, a different argument can be made when exploring possible limitations. To start, construct validity has to be discussed in order to provide a transparent discussion. This indicates whether the test measures the concept that it is intended to measure and whether it is fully representative of what it aims to measure (Nevo, 1985). While this study made use of pre-existing, validated scales to construct the experimental questionnaire, it may not suffice with regard to construct validity. Arguments can be made for this statement, as multiple variables violated normality. Five out of 12 variables in the conceptual model did not appear to be normally distributed, which may be due to improper operationalization of variables. To start, with regard to the three personality spectrums, two out of three variables displayed rather high means, which implies skewed results. For instance, with regard to conscientiousness, it is suggested that participants find themselves to be extremely organized and perseverant. This self-reporting bias can be explained by the self-presentational motive as introduced by Freud in 1914. This concept refers to how people present themselves to shape how others view them so that they become their 'ideal self'. This theory may have manifested itself in cognitive bias, thus skewing results. Additionally, in Chapter 4, a decision was made to adhere to findings from the confirmatory factor analysis, which found that personality scales increased in Cronbach's α, when certain items were to be deleted. The deletion of data means simultaneously discarding abundant data that has previously been validated by experts. However, the decision to comply with the CFA was justified as it would considerably increase the Cronbach's α of each individual component. Second, the outcome variable, namely behavioral intent, was complex to operationalize. Sharing private data is quite a controversial topic, thus it was foreseeable that the data was bimodally distributed. This means that while the mean of the variables measured was roughly centered, there were two peaks that categorized those who strongly felt about not sharing their private data and those who did not seem to mind sharing their private data. The non-normal distribution could have been approached differently by operationalizing this variable through a nominal dependent variable, so a logistic regression could have been conducted. However, a major downside with this approach is that the richness of data would decrease tremendously, as behavioral intent should be measured on a scale, as it is simply not a binary concept. With this consideration, behavioral intent remained a continuous variable. The normality of variables regarding both psychometrics and behavioral intent may have played a role in the outcomes of this study, as parametric analyses were conducted while the data set violated the assumptions for these analyses. This is justified by the theory of Ghasemi and Zahediaslv (2012), who state that with a large enough sample, the violation of normality should not cause major problems. Additionally, Pek et al. (2018) state that small violations may have little effect on the analysis and that non-normality is among the most common encounters in statistical studies, especially in psychology and related sciences. However, regardless of these arguments, transparency on the violation of normality is imperative.

A second limitation that transpired was that the sample was not representative of the Dutch population, meaning that it is difficult to generalize findings beyond this study. For instance, variables such as sex, age, educational level, and the residential area did not align with statistics representative of the Dutch population, according to Centraal Bureau voor de Statistiek (CBS, 2022). With regard to gender, more women partook in this experiment than men. This may informally implicate multiple things, for instance, that women are generally more motivated to help with research, or simply that the sampling technique reached more women than men. Furthermore, a discord with educational level may have contributed to a biased sample, which possibly manifests in higher scores on the personality spectrums. For instance, with conscientiousness, self-reported scores may have been higher than average, simply because the majority of the sample population is more conscientious than the average Dutch population. The overall sample disproportionately held diplomas in higher education, meaning that these individuals simply are more perseverant, organized, and hardworking. With that being said, there is an increased risk of systematic bias, implying that the results from this sample may be incompatible with the theoretical population (Malone et al., 2014).

Lastly, while a lot of care went into the curation of the experiment, a limitation that ensued was that the online experiment was conducted in Dutch. While the Big Five Personality scale has been verified in Dutch, the behavioral intent scale by Xu et al. (2011) had to be translated. There are possible challenges that come with translating question items for them to be psychometrically sound and effective to use in research (Tsang et al., 2017). While the items were transcribed with care, it was not translated verbatim to ensure readability. Therefore, it may be possible that some inklings were lost in translation. To limit the probability of this from occurring, pilot testing was employed, and slight alterations were made to ensure an accurate and representative item list. With that being said, not all psychometric properties from the original English item list may have carried over to the translated item list, which can be a disadvantage.

5.4. Suggestions for further research

Though this study did not reach its prospective potential, prior research does repeatedly show the positive effects of personality marketing in the consumption market (Hirsh et al., 2012; Matz et al., 2017;

Winter et al., 2021). Strong assumptions remain that personality can, in fact, be a predictor of one's willingness to disclose private data, and it is therefore suggested that further research on this concept should be conducted to explore possible clarifications and motives.

Rather than conducting an online experiment, a field experiment can be conducted to create a more realistic composition for participants. It is possible that participants had difficulties positioning themselves in a fictional situation and then making claims based on hypothetical scenarios. Since sharing one's private data is already a complicated and abstract concept, it may be difficult to accurately report their actual, subconscious beliefs. Data sharing occurs most frequently in everyday settings, thus transferring this research design into a field experiment may create more valid and legitimate data. Matz et al. (2017) conducted a field experiment on Facebook and managed to yield promising results, thus further investigating the variables in this thesis in a different setting may generate valuable insights. However, it is important to remember that conducting a field experiment may bring ethical obstacles, such as violating participants' privacy or creating false narratives in addition to not being able to provide informed consent.

As mentioned in Chapter 5.2.1, it appears that there may simply be too wide of a gap between prior research of personality marketing in the consumption market and in a high-involvement market such as the insurance sector. Not only is there a difference between tangible goods versus intangible contracts, but it may also feel as if there is more at stake when sharing health data compared to data concerning your car or similar items that one insures. In the focus group that was held before establishing the research design, experts in the insurance industry stated that investigating the health insurance industry was the most perceptible scope. While this appeared to be a rational decision, it may have caused discrepancies in findings. It seems that way as the focus group likely reasoned from a product perspective (i.e., health insurance resonates with all participants, as it is a mandatory product), rather than a client perspective (i.e., releasing health data is one of the most intimate sets of data one can share). Therefore, perhaps a different insurance sector, such as P&C, will provide significant findings that will allow a step forward in the understanding of the concept of data sharing. This shift of product focus, whether that be life or P&C insurance can be extended beyond the Netherlands as well, as insurance is a product that pertains to almost any individual regardless of their residential country. Furthermore, it could be interesting to explore possible differences in behavioral intent in countries where the GDPR is set in place compared to countries without strict privacy laws. As there has been substantial publicity regarding privacy laws in the European Union, it is possible that these citizens are more aware of their digital privacy rights compared to non-Europeans. Therefore, it may be possible that different results are derived from a similar study in different countries.

Besides adjusting the initial research design, a final suggestion would be to design a similar study, but simply to ensure the sample population is reflective of the society. As stated in the limitations, the sample in this study was evidently skewed, which may have impacted the validity of this study. Ensuring that the sample is representative allows for a more valid, and thus generalizable, study.

5.5. Conclusion

To conclude, this study did not find evidence to support theories that show the interaction effect of the self-determination theory on psychometrics and behavioral intent. Both the hypothesized main and interaction effects in this study did not reach significance, meaning that findings in this study contradicted academic and theoretical findings. Age, however, was found to be a significant predictor of willingness to disclose private data, which is a finding that has both academic and managerial implications. Mainly, it is worth noting that data is becoming inevitable, thus it is crucial that this concept is being researched to be able to understand the benefits and risks associated.

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Appendix A: Survey instrument in English

For my Master's Thesis at the Erasmus University Rotterdam, I am hoping to learn more about personalized marketing and the phenomenon of data sharing. I hope you are willing to help me by partaking in this research.

Partaking in this study will take roughly ten minutes of your time. There are no right or wrong answers, I am merely interested in your opinions. Your responses will remain anonymous and confidential and your name will not be associated with any research findings. The responses will be used for statistical analyses, and the results of this research will be reported in the Master's Thesis. At the end of this study, you will have the opportunity to provide feedback or any other comments. If you agree to participate, please be aware that you can still withdraw from the survey at any time by simply closing this tab. In this case, your information will be discarded and your answers will not be used as part of this research.

Clicking on the 'next' button indicates that:
- You are at least 18 years old
- You voluntarily agree to participate
- You have read and agree with the above information

If you complete this questionnaire, you will be able to win a Bol.com gift card with a value of €15,00. If you wish to not participate in this research, you can now exit out of this browser.

For SurveySwap.io users: This questionnaire has a SurveySwap.io code at the end of this research.

I appreciate your time and your participation.

Veerle van Oosterom

(Page break)

Experimental Condition 1: Extrinsic Motivation

Through the use of technological devices, like a smartphone and a laptop, we share more and more personal data. For example, when visiting a website, you oftentimes have to accept cookies and privacy declarations.

For this research project, you will be asked about your willingness to disclose personal data with a health insurer. On the next page, you will be presented with three situations. In exchange for sharing your personal data, you will be able to receive a discount on your premium. Every scenario presented should be considered separate, not cumulative.

It is important to note that it is forbidden by European privacy law to raise the prices of basic insurance based on personal data. If a health insurer knows about your smoking habits, they legally are not allowed to raise your premium. You are always within your right to adjust your data or to have your data removed entirely.

(Page break)

Scenario 1: Would you be willing to share your BMI (height and weight) with a health insurer, in return for 5% off your monthly premium?
Scenario 2: Would you be willing to share data on your lifestyle (in the form of a short questionnaire on your eating habits, for instance) with a health insurer, in return for 5% off your monthly premium?
Scenario 3: Would you be willing to share your health data (blood reports, for instance) with a health insurer, in return for 5% off your monthly premium?

1. I am interested to share X in return for 5% off my monthly premium
2. I feel the benefits gained from sharing X outweigh the risks of my disclosure
3. I feel the value I gain from sharing X is worth the information I give away
4. Overall, I feel that sharing X will be beneficial
5. I feel providing the insurer with X would involve many unexpected problems
6. I feel it would be risky to disclose X to the insurer
7. If it were possible, I would be willing to share X in return for 5% off my monthly premium

(Page break)

In the hypothetical situation that was presented, you were presented with a reward in exchange for sharing private data. What was this reward?

- Five percent discount on monthly premium
- Being able to contribute to the improvement of the insurance

Experimental Condition 2: Intrinsic Motivation

Through the use of technological devices, like a smartphone and a laptop, we share more and more personal data. For example, when visiting a website, you oftentimes have to accept cookies and privacy declarations.

For this research project, you will be asked about your willingness to disclose personal data with a health insurer. The more people willing to share their personal data, the more the insurer will be able to improve the health insurance. And thus, the better the health insurance, the more people will benefit from it. This might lead you to feel satisfaction and acknowledgment.

It is important to note that it is forbidden by European privacy law to raise the prices of basic insurance based on personal data. If a health insurer knows about your smoking habits, they legally are not allowed to raise your premium. You are always within your right to adjust your data or to have your data removed entirely.

(Page break)

Scenario 1: Would you be willing to share your BMI (height and weight) with a health insurer, to contribute to the improvement of the insurance?
Scenario 2: Would you be willing to share data on your lifestyle (in the form of a short questionnaire on your eating habits, for instance) with a health insurer, to contribute to the improvement of the insurance?
Scenario 3: Would you be willing to share your health data (blood reports, for instance) with a health insurer, to contribute to the improvement of the insurance?

1. I am interested to share X to be able to contribute to the improvement of the insurance
2. I feel the benefits gained from sharing X outweigh the risks of my disclosure
3. I feel the value I gain from sharing X is worth the information I give away
4. Overall, I feel that sharing X will be beneficial
5. I feel providing the insurer with X would involve many unexpected problems
6. I feel it would be risky to disclose X to the insurer
7. If it were possible, I would be willing to share X to be able to contribute to the improvement of the insurance

(Page break)

If I can contribute to the improvement of the insurance, so that all its users can benefit from it, will give me a good feeling
- Yes
- No

In the hypothetical situation that was presented, you were presented with a reward in exchange for sharing private data. What was this reward?
- Five percent discount on monthly premium
- Being able to contribute to the improvement of the insurance

Control group

Through the use of technological devices, like a smartphone and a laptop, we share more and more personal data. For example, when visiting a website, you oftentimes have to accept cookies and privacy declarations.

For this research project, you will be asked about your willingness to disclose personal data with a health insurer. On the next page, you will be presented with three situations. Please, carefully read each description and all questions for every scenario.

It is important to note that it is forbidden by European privacy law to raise the prices of basic insurance based on personal data. If a health insurer knows about your smoking habits, they legally are not allowed to raise your premium. You are always within your right to adjust your data or to have your data removed entirely.

(Page break)

<u>Scenario 1:</u> Would you be willing to share your BMI (height and weight) with a health insurer?
<u>Scenario 2:</u> Would you be willing to share data on your lifestyle (in the form of a short questionnaire on your eating habits, for instance) with a health insurer?
<u>Scenario 3:</u> Would you be willing to share your health data (blood reports, for instance) with a health insurer?

1. I am interested to share X
2. I feel the benefits gained from sharing X outweigh the risks of my disclosure
3. I feel the value I gain from sharing X is worth the information I give away
4. Overall, I feel that sharing X will be beneficial
5. I feel providing the insurer with X would involve many unexpected problems
6. I feel it would be risky to disclose X to the insurer
7. If it were possible, I would be willing to share X

Continuation of the experiment for all participants

Below are a number of characteristics presented that may or may not apply to you. For example, do you agree that you are someone who likes to spend time with others? Then you would fill in '*strongly agree*'. There are no right or wrong answers.

1. Tends to find fault with others
2. Does a thorough job
3. Is depressed, blue
4. Is helpful and unselfish, with others
5. Can be somewhat careless
6. Is relaxed, handles stress well
7. Starts quarrels with others
8. Is a reliable worker
9. Can be tense
10. Has a forgiving nature
11. Tends to be disorganized
12. Worries a lot
13. Is generally trusting
14. Tends to be lazy
15. Is emotionally stable, not easily upset
16. Can be cold and aloof
17. Perseveres until the task is finished
18. This is an attention check, please tick 'disagree'
19. Can be moody
20. Is considerate and kind to almost everyone
21. Does things differently
22. Remains calm in tense situations
23. Is sometimes rude to others
24. Makes plans and follows through with them
25. Gets nervous easily
26. Likes to cooperate with others
27. Is easily distracted

(Page break)

Lastly, a few demographical questions are presented. Please remember that your answers to these questions will remain completely anonymous.

What gender do you best identify with?

- Male
- Female
- Non-binary / third gender
- Prefer not to say

What is your age?

What is the highest level of education you have obtained?

- Less than a high school diploma
- High school or equivalent
- Some education but no diploma
- Bachelor's degree
- Graduate degree or higher
- No diploma or higher education
- Prefer not to say

What is your marital status?
- Single
- Registered partnership
- Married
- Divorced
- Widowed
- I’d rather not say
- Other, namely

Which of the following options best represents the area you live in?
- A large city (over 100.000 citizens, examples are Utrecht, Tilburg, Haarlem, Arnhem and Leiden)
- A small city
- A village
- The countryside
- Other, namely
- I’d rather not say

Are you currently in the possession of a smartwatch (like, an Apple Watch, Samsung Watch or a FitBit)?
- Yes
- No

Are you currently consciously sharing personal data?
- Yes
- No

Research has shown that on average thousands of data points are extracted from a single user. Think about engagement (likes, comments or shares), consumer behavior (clicks on advertisements), and characteristics (participating in polls or quizzes).

Are you aware of the amount of personal data that is being collected?
- Yes
- No

(Page break)

Thank you for taking time to participate in this research. The aim of this study is to investigate whether someone’s personality traits affect someone’s willingness to disclose private data. During this experiment, you were assigned to one of three groups: The first group was presented with a 5% discount on their monthly premium if they were willing to share their private data (extrinsic reward). Participants assigned to the second group were told that they would help improve the insurer’s product, namely the health care insurance, for all users (intrinsic reward). The last group was a control group, meaning that these participants were not presented with any reward. The willingness to disclose private data will be compared with personality traits and the self-determination theory, so that the research question of this study can be answered.

Leave your e-mail address in the input field below to partake in the lottery for a Bol.com gift card. The winner of this lottery will receive a digital gift card worth €15,00 in their inbox within three weeks.

If you have any further questions or remarks regarding the survey or the research, you will be able to (anonymously) share them in the text input field below. You will also be able to send me an e-mail, at 593484@eur.student.nl

For SurveySwap.io users: the following code will give you credits that can be used for participants of your research. Go to: https://surveyswap.io/sr/WHVJ-5YSA-ZNRM or fill in the code by hand: WHVJ-5YSA-ZNRM

Please, enter your e-mail address if you would like to join the lottery. You will also be able to share questions and/or remarks here.

Your answers have been saved successfully. Thank you for your time, your participation is highly appreciated.

Veerle van Oosterom, 593484vo@student.eur.nl

Appendix B: Survey instrument in Dutch

Voor mijn MA afstudeerscriptie aan de Erasmus Universiteit Rotterdam doe ik onderzoek naar gepersonaliseerde marketing en het fenomeen van data delen. Ik hoop dat u mij wilt helpen door aan dit onderzoek deel te nemen.

Het invullen van deze vragenlijst duurt ongeveer 10 minuten. Er zijn geen goede of foute antwoorden, ik ben alleen geïnteresseerd in uw mening. Uw antwoorden op de vragen zijn volledig anoniem en vertrouwelijk. De resultaten van deze vragenlijst zullen alleen worden gebruikt voor analyses voor mijn scriptie. Aan het eind van de vragenlijst is er ruimte om eventuele opmerkingen te maken en/of vragen te stellen. Als u deelneemt aan dit onderzoek kunt u op elk moment stoppen met deze vragenlijst. In dat geval worden uw antwoorden verwijderd en zullen ze niet worden gebruikt in de analyses van het onderzoek.

Als u doorgaat door op het pijltje te klikken, betekent het dat:
- U de bovenstaande informatie heeft gelezen en hiermee akkoord gaat
- U vrijwillig besluit deel te nemen aan dit onderzoek
- U minimaal 18 jaar oud bent

Als u deze vragenlijst volledig invult, maakt u kans op een Bol.com cadeaubon ter waarde van €15,00. Als u niet wilt deelnemen aan dit onderzoek, kunt u nu dit tabblad sluiten.

Voor SurveySwap.io gebruikers: Dit onderzoek bevat een SurveySwap.io code aan het eind van deze vragenlijst.

Ik stel uw deelname erg op prijs.

Veerle van Oosterom

(Pagina onderbreking)

Experimentele Groep 1: Extrinsieke motivatie
Via het gebruik van technologische apparaten, zoals een smartphone en een laptop, delen we steeds meer persoonlijke gegevens. Als u bijvoorbeeld een website bezoekt, moet u vaak de cookies en privacyverklaringen accepteren.

In dit onderzoek wordt gevraagd naar uw bereidheid om persoonlijke gegevens te delen met een zorgverzekeraar in drie verschillende situaties. In ruil voor het delen van uw gegevens kunt u korting krijgen op uw premie. Elke situatie is losstaand, en dus niet cumulatief.

Het is goed om te weten dat het volgens Europese privacywetten verboden is om prijzen van basisverzekeringen te verhogen op basis van persoonlijke gegevens. Als een verzekeraar bijvoorbeeld weet dat u rookt, mag hij uw premie niet verhogen. U heeft altijd het recht om deze gegevens aan te passen of te laten verwijderen.

(Pagina onderbreking)

Scenario 1: Zou u uw BMI (gewicht en lengte) willen delen met een zorgverzekeraar, in ruil voor 5% korting op uw maandelijkse premie?
Scenario 2: Zou u gegevens over uw levensstijl (bijvoorbeeld in de vorm van een korte vragenlijst over uw eetpatroon) willen delen met een zorgverzekeraar, in ruil voor 5% korting op uw maandelijkse premie?
Scenario 3: Zou u gegevens over uw gezondheidsgegevens (bijvoorbeeld bloeduitslagen en cholesterolgehaltes) willen delen met een zorgverzekeraar delen, in ruil voor 5% korting op uw maandelijkse premie?

1. Ik sta ervoor open om X te delen in ruil voor 5% korting
2. Ik denk dat de voordelen van het delen van X opwegen tegen de risico’s
3. Ik denk dat het risico van het delen van X groter is dan de verwachte waarde
4. Al met al denk ik dat het delen van X het waard is
5. Ik denk dat het delen van X met de verzekeraar veel onverwachte problemen met zich mee zal brengen
6. Ik denk dat het riskant kan zijn om X met de verzekeraar te delen
7. Als het mogelijk was zou ik X verstrekken in ruil voor 5% korting

(Pagina onderbreking)

In het voorbeeld werd u verteld dat u een beloning zou krijgen voor het delen van uw persoonlijke gegevens. Wat was deze beloning?

- Vijf procent korting op uw maandelijkse premie
- Het kunnen bijdragen aan de verbetering van de verzekering

Experimentele Groep 2: Intrinsieke motivatie
Via het gebruik van technologische apparaten, zoals een smartphone en een laptop, delen we steeds meer persoonlijke gegevens. Als u bijvoorbeeld een website bezoekt, moet u vaak de cookies en privacyverklaringen accepteren.

In dit onderzoek wordt gevraagd naar uw bereidheid om persoonlijke gegevens te delen met een zorgverzekeraar. Hoe meer mensen dit doen, hoe beter de zorgverzekeraar de verzekering kan maken. En hoe beter de verzekering is, des te meer mensen daarvan profiteren. Dit kan bij u leiden tot gevoelens van voldoening en erkenning.

Het is goed om te weten dat het volgens Europese privacywetten verboden is om prijzen van basisverzekeringen te verhogen op basis van persoonlijke gegevens. Als een verzekeraar bijvoorbeeld weet dat u rookt, mag hij uw premie niet verhogen. U heeft altijd het recht om deze gegevens aan te passen of te laten verwijderen.

(Pagina onderbreking)

Scenario 1: Zou u uw BMI (gewicht en lengte) willen delen met een zorgverzekeraar, om zo bij te dragen aan het verbeteren van de verzekering voor alle klanten?
Scenario 2: Zou u gegevens over uw levensstijl (bijvoorbeeld een korte vragenlijst over uw eetpatroon) willen delen met een zorgverzekeraar, om zo bij te dragen aan het verbeteren van de verzekering voor alle klanten?
Scenario 3: Zou u uw gezondheidsgegevens (bijvoorbeeld bloeduitslagen en cholesterolgehaltes die uw huisarts kan verstrekken) willen delen met een zorgverzekeraar, om zo bij te dragen aan het verbeteren van de verzekering voor alle klanten?

1. Ik sta ervoor open om X te delen, om zo bij te dragen aan het verbeteren van de verzekering, zodat alle klanten hiervan kunnen profiteren
2. Ik denk dat de voordelen van het delen van X opwegen tegen de risico's
3. Ik denk dat het risico van het delen van X groter is dan de verwachte waarde
4. Al met al denk ik dat het delen van X het waard is
5. Ik denk dat het delen van X met de verzekeraar veel onverwachte problemen met zich mee zal brengen
6. Ik denk dat het riskant kan zijn om X met de verzekeraar te delen
7. Ik zou X delen met de verzekeraar, om zo bij te dragen aan het verbeteren van de zorgverzekering, zodat alle klanten hiervan kunnen profiteren

Als ik kan helpen om de verzekering te verbeteren, zodat alle gebruikers daarvan kunnen profiteren, geeft mij dat een goed gevoel

- Ja
- Nee

In het voorbeeld werd u verteld dat u een beloning zou krijgen voor het delen van uw persoonlijke gegevens. Wat was deze beloning?

- Vijf procent korting op uw maandelijkse premie
- Het kunnen bijdragen aan de verbetering van het product

Controle Groep

Via het gebruik van technologische apparaten, zoals een smartphone en een laptop, delen we steeds meer persoonlijke gegevens. Als u bijvoorbeeld een website bezoekt, moet u vaak de cookies en privacyverklaringen accepteren.

In dit onderzoek zal worden gevraagd naar uw bereidheid om persoonlijke gegevens te delen met een zorgverzekeraar. Er zullen op de volgende pagina drie situaties worden gepresenteerd. Lees alstublieft bij elk scenario de omschrijving en vragen goed.

Het is belangrijk om te weten dat het volgens Europese privacywetten verboden is om prijzen van basisverzekeringen te verhogen op basis van persoonlijke data. Als een verzekeraar bijvoorbeeld weet dat u rookt mag hij uw premie niet verhogen. U heeft altijd het recht om deze gegevens aan te passen of te laten verwijderen.

(Pagina onderbreking)

Scenario 1: Zou u uw BMI (gewicht en lengte) willen delen met een zorgverzekeraar?
Scenario 2: Zou u gegevens over uw levensstijl (bijvoorbeeld een korte vragenlijst over uw eetpatroon) willen delen met een zorgverzekeraar?
Scenario 3: Zou u uw gezondheidsgegevens (bijvoorbeeld bloeduitslagen en cholesterolgehaltes die uw huisarts kan verstrekken) willen delen met een zorgverzekeraar?

Vervolg van het experiment voor alle respondenten
Hieronder staan een aantal stellingen die wel of niet van toepassing zullen zijn op uw persoonlijkheid. Bent u bijvoorbeeld iemand die erg graag tijd doorbrengt met anderen? Dan vult u 'sterk mee eens' in. Er zijn geen goede of foute antwoorden.

1. Heeft de neiging om fouten bij anderen te zoeken
2. Doet grondig werk
3. Is depressief, blauw
4. Is behulpzaam en onbaatzuchtig, met anderen
5. Kan wat onvoorzichtig zijn
6. Is ontspannen, kan goed met stress om
7. Begint ruzie met anderen
8. Is een betrouwbare werker
9. Kan gespannen zijn
10. Heeft een vergevingsgezind karakter
11. Heeft de neiging om ongeorganiseerd te zijn
12. Maakt zich veel zorgen
13. Heeft over het algemeen vertrouwen
14. Neiging om lui te zijn
15. Is emotioneel stabiel, niet snel van streek
16. Kan koud en afstandelijk zijn
17. Volhardt totdat de taak is voltooid
18. Dit is een controlevraag, vul hier 'oneens' in
19. Kan humeurig zijn
20. Is attent en aardig voor bijna iedereen
21. Doet het anders
22. Blijft kalm in gespannen situaties
23. Is soms onbeleefd tegen anderen
24. Maakt plannen en volgt ze op
25. Wordt snel nerveus
26. Werkt graag samen met anderen
27. Is snel afgeleid

(Pagina onderbreking)

Tot slot volgen er een aantal demografische en afsluitende vragen. Onthoud dat uw antwoorden op deze vragen volledig anoniem zijn.

Wat is uw geslacht?
- Man
- Vrouw
- Non-binair
- Anders
- Wil ik liever niet zeggen

Wat is uw leeftijd?

Wat is het opleidingsniveau waar u momenteel voor studeert of het diploma voor heeft behaald?
- VMBO / VBO / MAVO (of een vergelijkbare opleiding)
- MBO (of een vergelijkbare opleiding)
- HAVO / VWO
- HBO (Hogeschool) / WO (Universiteit)
- Post-HBO / Post-WO
- Niet van toepassing
- Wil ik liever niet zeggen

Wat is uw burgerlijke staat?
- Alleenstaand
- Partnerschap
- Gehuwd
- Gescheiden
- Weduwe/Weduwnaar
- Wil ik liever niet zeggen
- Anders, namelijk

Welke van de onderstaande opties past het best bij de omgeving waar u woont?
- Een grote stad (met meer dan 100.000 inwoners, enige voorbeelden zijn Utrecht, Tilburg, Haarlem, Arnhem, en Leiden)
- Een kleine stad
- Een dorp
- Het platteland
- Anders, namelijk
- Wil ik liever niet zeggen

Beschikt u op dit moment over een smartwatch (bijvoorbeeld een Apple Watch, Samsung Watch of FitBit)?
- Ja
- Nee

Deelt u op dit moment al bewust data?
- Ja
- Nee

Uit onderzoek is gebleken dat van een gemiddelde gebruiker van een sociaal platform duizenden datapunten verzameld worden. Denk hierbij aan data over engagement (liken, reageren of delen), consumentengedrag (klikken op advertenties) en karaktereigenschappen (deelnemen aan polls of quizzen).

Bent u er zich van bewust hoeveel persoonlijke data er van u wordt verzameld?
- Ja
- Nee

(Pagina onderbreking)

Bedankt voor het invullen van deze vragenlijst. Het doel van deze scriptie is om te onderzoeken of de persoonlijkheidskenmerken van iemand van invloed zijn op de bereidheid om persoonsgegevens te delen. Tijdens dit experiment bent u ingedeeld in één van drie groepen: De eerste groep kreeg als beloning 5% korting op de basisverzekering bij het delen van persoonsgegevens (extrinsieke beloning). Deelnemers uit de tweede groep kregen te horen dat zij zouden bijdragen aan het verbeteren van de zorgverzekering (intrinsieke beloning). De derde groep was een controlegroep, die geen beloning zou krijgen voor het delen van gegevens. De bereidheid tot het delen van persoonsgegevens zal worden geanalyseerd met de persoonlijkheidskenmerken van de deelnemer en de zelfdeterminatietheorie, waardoor de onderzoeksvraag van mijn scriptie zal worden beantwoord.

Laat in het tekstvak hieronder uw e-mailadres achter als u mee wilt doen aan de winactie van de Bol.com cadeaubon. De winnaar ontvangt binnen drie weken een digitale cadeaubon ter waarde van €15,00 via uw e-mail.

Mocht u verder opmerkingen en/of vragen hebben over de vragenlijst of mijn onderzoek, deel deze dan (anoniem) in het onderstaande tekstvak of stuur een e-mail (niet anoniem) naar 593484vo@eur.student.nl

Voor SurveySwap.io gebruikers: De volgende code geeft u kredieten die gebruikt kunnen worden voor deelnemers aan uw onderzoek. Ga naar: https://surveyswap.io/sr/WHVJ-5YSA-ZNRM of vul de code handmatig in: WHVJ-5YSA-ZNRM

Vul hier alstublieft uw e-mail in als u mee wilt doen aan de winactie. Ook kunt u hier enige opmerkingen en/of vragen delen.

Uw antwoorden zijn succesvol opgeslagen. Ik dank u voor uw tijd, uw deelname wordt erg op prijs gesteld.

Veerle van Oosterom, 593484vo@student.eur.nl

Appendix C: Focus group with experts

To determine which insurance product was going to be used for this research, a “mini-focus group” was held with three senior employees of Nationale-Nederlanden, one of the largest insurance companies in the Netherlands that offers all lines of insurances. Holding a focus group is a way to collect qualitative data in a semi-informal environment to discuss opinions and thoughts among professionals (Onwuegbuzie et al., 2009). A benefit from holding a focus group is that they are often fast and efficient (Krueger & Casey, 2000), and allow for great flexibility. The goal of this focus group was to form a consensus to choose one of three insurance products that would help design a unambiguous hypothetical quantitative experiment.

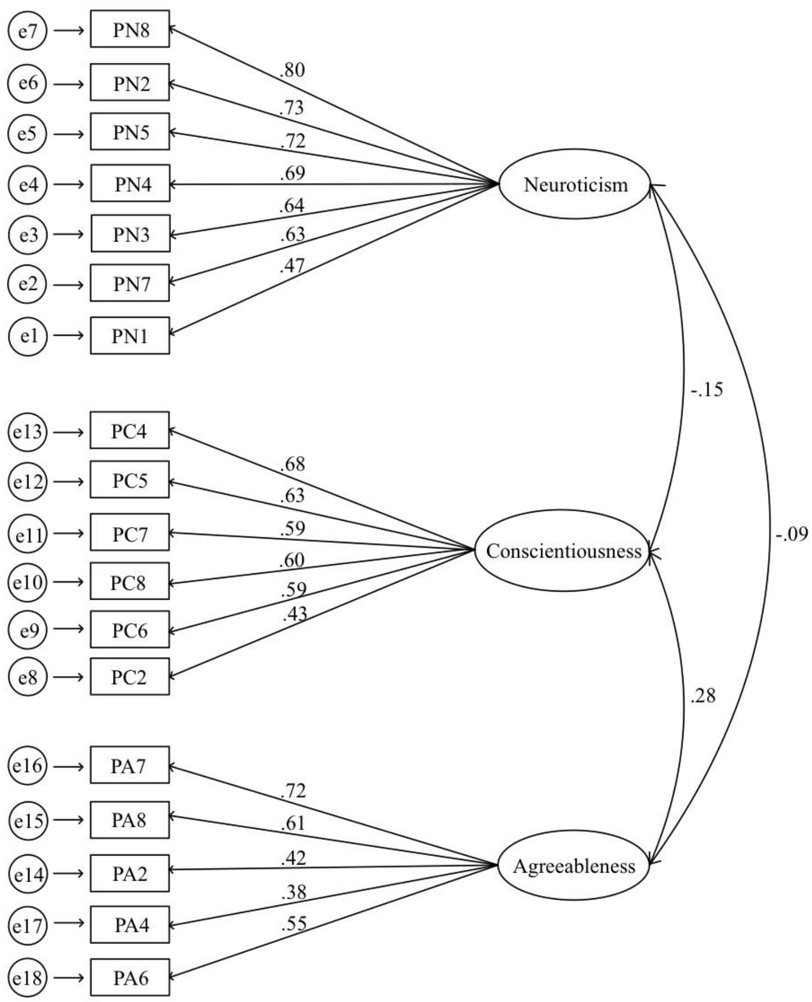
While focus groups usually last an hour to two hours (Onwuegbuzie et al., 2009), this focus group lasted around 40 minutes and was held over Microsoft Teams on March 11, 2022. The reason for the meeting being held remotely was due to the fact that Nationale-Nederlanden still has Covid-19 restrictions in place, which allow employees to work from home. During the online meeting, group interaction data was obtained which would to look at argumentative interactions that provide rich data (Duggleby, 2005).

Prior to the start of the focus group, a brief introduction between the researcher and participants transpired. Then, the research subject and a broad outline of this study was provided to inform participants on this aim of this thesis. During the focus group, it was discussed that insurance is a broad industry, and that their products and their target groups differ greatly between the different lines of insurance. It soon became apparent that while the Life business line has an enormous market share, its target audience and the way its products are distributed, made it less of a match. Pension plans are marketed to employers, but direct sales are not possible: advice from brokers is legally required and they are the Life department’s only direct business partner. As this research is focused on consumers’ attitude towards data, this excluded the Life business line. The same held true for disability insurance, commercial damage insurance and other commercial lines of insurance: their target groups made them less than a perfect match for this research.

The target group subsequently focused on personal lines of insurance, namely personal damage insurance and health insurance. Target audience, product characteristics, and distribution approach of both lines were discussed and considered. While the participants could see merit in both, they favored health insurance for several reasons. First, the sheer size of the target audience, as every individual in the Netherlands is required to have health insurance, whereas personal damage insurance is optional and thus a much smaller business line. Second, while personal damage insurance is considered to be a low-interest product, people are more invested in health insurance as this directly relates to their well-being. Hence, the participants in the focus group thought that health insurance would probably resonate better with respondents to the survey. Third, the marketing budget for health insurance is many times that of personal damage insurance, which made the participants believe that the health insurance department would ultimately be able to work more effectively, making it the main focus of this thesis.

Often times, analyzing qualitative data derived from focus groups can be challenging (Onwuegbuzie et al., 2009), however this focus group had a clear, unanimous outcome. As the duration of this mini-focus group was shorter than average focus groups, and had fewer participants, it was quite straightforward analyzing derived data and to make justified decisions regarding the operationalization of the experiment.

Appendix D: AMOS 26 Results



CMIN

	NPAR	*CMIN*	*DF*	*P CMIN/DF*
Default model	57	321.894	.000	2.439
Saturated model	189	.000	0	.
Independence model	36	1405.980	.000	9.189

Baseline Comparisons

	NFI Delta 1	*RFI rho1*	*IFI Delta 2*	*TLI rho 2*	*CFI*
Default model	.771	.735	.851	.824	.848
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

	PRATIO	*PNFI*	*PCFI*
Default model	.863	.665	.732
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

NCP

	NCP	*LO90*	*HI90*
Default model	189.894	141.073	246.413
Saturated model	.000	.000	.000
Independence model	1252.980	1136.705	1376.686

FMIN

	FMIN	*F0*	*LO 90*	*HI 90*
Default model	1.277	.754	.560	.978
Saturated model	.000	.000	.000	.000
Independence model	5.579	4.972	4.511	5.463

RMSEA

	RMSEA	*LO90*	*HI90*	*PCLOSE*
Default model	.076	.065	.086	.000
Independence model	.180	.172	.189	.000

AIC

	AIC	*BCC BIC CAIC*
Default model	435.894	445.190
Saturated model	378.000	408.824
Independence model	1477.980	1483.851

ECVI

	ECVI	*LO90*	*HI90*	*MECVI*
Default model	1.730	1.536	1.954	1.767
Saturated model	1.500	1.500	1.500	1.622
Independence model	5.865	5.404	6.356	5.888

Appendix E: One-way between subjects ANOVA model summary

	Sum of Squares	*df*	*Mean Square*	*F*	*Sig*
Between groups	39.90	5	7.98	3.58	.004
Within groups	549.95	247	2.28		
Total	589.85	252			

Age		*Mean Difference*	*Std. Error*	*Sig.*
18 - 22	23 - 26	.234	.308	.974
	27 - 32	.713	.405	.494
	33 - 45	.890	.324	.076
	46 - 56	1.067*	.307	.008
	57 - 86	.840	.328	.110
23 - 26	18 - 22	-.234	.308	.974
	27 - 32	.479	.392	.825
	33 - 45	.645	.306	.287
	46 - 56	.833*	.289	.048
	57 - 86	.606	.310	.373
27 - 32	18 - 22	-.713	.405	.494
	23 - 26	-.479	.392	.825
	33 - 45	.166	.404	.998
	46 - 56	.354	.391	.945
	57 - 86	.127	.407	1.000
33 - 45	18 - 22	-.879	.324	.076
	23 - 26	-.645	.306	.287
	27 - 32	-.166	.404	.998
	46 - 56	.188	.305	.990
	57 - 86	-.040	.326	1.000
46 - 56	18 - 22	-1.067*	.307	.008
	23 - 26	-.833*	.289	.048
	27 - 32	-.354	.391	.945
	33 - 45	-.188	.305	.990
	57 - 86	-.228	.309	.977
57 - 86	18 - 22	-8.40	.328	.110
	23 - 26	-.606	.310	.373
	27 - 32	-.127	.407	1.000
	33 - 45	.040	.326	1.000
	46 - 56	.228	.309	.977

Note *. Mean difference is significant at the 0.05 level.