Master's thesis

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How Cultural Factors Influence Consumer Autonomy: A Quantitative Analysis

Master's thesis in International Business & Marketing

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Preface

This master thesis symbolizes the very end of our time at the NTNU Ålesund. After five eventful years here, we can finally state that we are moving towards an achieved Master of Science in International Business & Marketing. The beginning of this course was during a time where a pandemic prevented physical instructions at school, and to meet our professors and fellow students in person. Despite this challenging start, the semesters have gone by. Suddenly, our very nice group of students was eligible to start their master´s thesis.

With both possessing a genuine interest in technological developments and consumer behavior, the research topic was thus heavily influenced by this. Different attempts and approaches to conduct the thesis have been made, but eventually after several discussions and ideas, we are really happy about our work.

A huge thanks to our supervisor Mark Pasquine for excellent guidance and feedback during this process. His great knowledge and competences have been very decisive to us. In addition, his genuine belief and optimism regarding our idea has been very motivating.

Abstract

Purpose - The purpose of this study is to validate and analyze how cultural factors influence the level of consumer autonomy

Design/approach - The research question was divided into four hypotheses and answered by a quantitative approach, where a questionnaire was distributed via Facebook and other social media platforms. Additionally, an Adaptive Conjoint Analysis was conducted to provide context to external factors and test the importance of consumer autonomy. Data was gathered from 104 respondents from Norway, and analyzed using SPSS.

Findings - The most important findings were through the hypotheses that proved that the dimensions of power distance, individualism and masculinity all have a statistically significant positive contribution in explaining consumer autonomy.

Originality/reliability: Research with information about the main purpose of this thesis is very limited. Hours of research resulted in the same result: Little to no literature contained concrete information about the relationship between the cultural dimensions and consumer autonomy. The positive thing about this is that we are able to analyze and present a unique contribution to our research. On the other hand, this large gap makes it somewhat more difficult to implement a representative basis for all hypotheses. It is therefore emphasized that theory of autonomy on its general basis will be applied, together with theoretical and logical approaches to be able to suggest how the six cultural dimensions contribute to predicting the degree of consumer autonomy, in our analyzes. When it comes to reliability, literature was only retrieved from articles through Google Scholar and NTNU Oria. This was to ensure a reliable and valid literature review that creates the foundation for a representative paper within future research.

Keywords - consumer, autonomy, culture, cultural dimensions, artificial intelligence,

Sammendrag

Formål - Hensikten med denne studien er å validere og analysere hvordan kulturelle faktorer påvirker nivået av forbrukerautonomi.

Design/tilnærming – Forskningsspørsmålet ble delt inn i fire hypoteser og besvart med en kvantitativ tilnærming, hvor et spørreskjema ble distribuert via Facebook og andre sosiale medieplattformer. I tillegg ble det utført en Adaptive Conjoint Analysis for å gi kontekst til eksterne faktorer og teste viktigheten av forbrukerautonomi. Data ble samlet inn fra 104 respondenter fra Norge, og analysert med SPSS.

Funn – De viktigste funnene var gjennom hypotesene som beviste at dimensjonene maktdistanse, individualisme og maskulinitet alle har et statistisk signifikant positivt bidrag til å forklare forbrukerautonomi.

Originalitet/pålitelighet - Forskning med informasjon om hovedformålet med denne oppgaven er svært begrenset. Timer med forskning resulterte i samme resultat: Lite eller ingen litteratur inneholdt konkret informasjon om forholdet mellom de kulturelle dimensjonene og forbrukerautonomi. Det positive med dette er at vi er i stand til å analysere og presentere et unikt bidrag til vår forskning. På den annen side gjør dette store gapet det noe vanskeligere å implementere et representativt grunnlag for alle hypoteser. Det understrekes derfor at teori om autonomi på dets generelle grunnlag vil bli anvendt, sammen med teoretiske og logiske tilnærminger for å kunne foreslå hvordan de seks kulturelle dimensjonene bidrar til å forutsi graden av forbrukerautonomi, i våre analyser. Når det gjelder pålitelighet, ble litteratur kun hentet fra artikler gjennom Google Scholar og NTNU Oria. Dette for å sikre en pålitelig og pålitelig litteraturgjennomgang som danner grunnlaget for en representativ artikkel innen fremtidig forskning.

Nøkkelord - forbruker, autonomi, kultur, kulturelle dimensjoner, kunstig intelligens,

Lists of tables

1. Introduction

Visualize you bought a product online you were recommended from a website, and the package on its way. After a few days it arrives, and you are excited to use it. Later that month you experience that the product is not that useful anymore, because it was not that useful as expected. Through further reasoning, you eventually realize that "why on earth did I buy this"

This speaks for a typical everyday example of artificial intelligence recommendation that tracks consumers' online behavior in order to market and sell products. While some are more unaffected by such content, others are perhaps more sensitive to being influenced, thus resulting in buying products they need much less than they consider at the time of purchase. This scenario involves consumers giving away their level of self-determination, which means that the AI marketing has made its entrance in their own decision making. On other hand, many consumers like to think of themselves and their actions as if they had free will (Wegner, 2004), and to consider these actions as internally driven and free from external influence (Wegner & Wheatley, 1999). Furthermore, consumers are also motivated to ascribe intent and responsibility (Wegner et al., 2004: Clark et al., 2014), and many tend to have a certain degree of autonomy.

But who are those who prefer to make autonomous decisions, and who are those who stand on the opposite side, or in between? What personal characteristics distinguish their view on consumer autonomy? This question will be analyzed in this master thesis by using Hofstede's six cultural dimensions, the paper will discover the relationship between the degree of consumer autonomy and the corresponding degree of how the six cultural dimensions play a role in influencing autonomy.

The evolution of artificial intelligence is constantly growing into consumers' user experiences today. Advances in technology and data collection mean that consumers are exposed to several external influences on the Internet. If you have looked at one shoe a little longer than the other, you should still not be surprised to receive digital advertising for both of them, during your further online surfing. In the end, all the benefits of products become so "good" that you finally perhaps get carried away and decide to buy. When AI is present, 49% of us are likely to shop more frequently (Brooks, 2020). Naturally, such scenarios are the alpha omega for companies. On the other hand, such methods pose a threat to consumers' internal influences and decisions about their self-determination and purchasing choices. Furthermore, where some perceive that they managed to make their own choices unaffected, others think it can be very externally influenced is very appropriate. Therefore, what characteristics distinguish the perceptions between each other?

1.1 Purpose of the study

The purpose of this study is to analyze culture and consumer autonomy in relation to each other. Further, the culture concept was addressed using Geert Hofstede's six cultural dimensions, in order to have a cultural scale. Autonomy is perceived and indicates the degree of consumer autonomy. By this, the following research question is:

RQ: Do cultural factors influence the level of consumer autonomy?

2. Literature review

This section will concern theoretical cultural preferences and differences regarding autonomous consumer choices. This topic, reflecting the research problem, is highly relevant for future research in literature (Davenport et al., 2029: Puntoni et al., 2020: Mishra et al., 2020). Not only do cultures consist of different expectations and perceptions about products and services in consumer behavior (de Mooji & Hofstede, 2002: Fang et al., 2013), they also vary the degree of autonomous consumer choices and react differently to autonomy and freedom of choice (Markus & Schwartz, 2010). In addition, a single culture can also have variations on autonomy (Wertenbroch et al., 2020). In other words, perceptions on autonomous choices vary within and across cultures, and this also suggests the paper´s research problem is highly relevant.

Additionally, other external factors that influence autonomy, such as privacy and AI, are included in the section.

2.1 Artificial intelligence

The term artificial intelligence (AI) refers to the technology that is capable of performing tasks and activities, previously thought possible only for humans. AI can be defined as "the use of computerized machinery to emulate capabilities once unique to humans" (Rust, 2019), through exploiting the ability of machines to carry out tasks by displaying intelligent, human-like behavior (e.g., machine learning, computer vision, speech recognition, and natural language processing) (Russell, 2016). Whereas intelligence is famously defined as "the ability to acquire and apply knowledge and skills" (Helskyaho et. al, 2021), artificial intelligence is, in short words, machines´ and technologies´ ability to act intelligent and use the skills learned. To successfully perform AI, this is dependent on the concepts of machine learning, big data and deep learning, which will be presented further below.

2.1.1 Artificial intelligence in marketing

From a business perspective, the implementation of AI in marketing is increasing as well as gaining importance for competitive firms worldwide (Huang & Rust, 2020) (Vlacic et. al, 2021). Today, AI is a tremendous option for companies to identify, analyze, convert and retain customers and offer a great boost in productivity (Nair & Gupta, 2021). AI marketing is present when businesses use the technologies to perform automated activities and make decisions based on data collection of users´ online activity (Pradeep et. al, 2019: Huang & Rust, 2020). This concept is often used to identify themes and patterns in users ‘posts about their product experience, providing a company with useful insights about their products´ success rate and interest (Wilson, 2016).

Being able to apply AI marketing, one depends on *machine learning* and *big data* to collect the relevant information about user activity. First of all, one can reckon machine learning as the foundation of artificial intelligence. The term describes the theory of which computers can learn without being programmed to carry out specific tasks. While AI is a concept of intelligent machines that simulate human thinking and behavior, machine learning is rather an application of a subset of AI that allows machines to automatically learn from past data without being explicitly programmed (Panesar, 2020). In other words, machine learning is a subset of AI where computer models are trained on the basis of past experience and actions and environment over time in order to perform their tasks. A machine learning example from a marketing operation can be if one was being taught about customer patterns in user activities on a website, machine learning can find these patterns and provide us information to predict future behavior of the users. This, in accordance with the theory, machine learning uses past experience/situations to predict future outcomes, providing marketers to be updated and prepared to quickly optimize their advertising.

The other term, big data, can be defined as “high-volume, high-velocity and high-variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making” (Yin & Kaynak, 2015) As big data can contain massive volumes of datasets, real-time data and different sources of data, the term is by this often described in terms of the three Vs: volume, velocity and variety. Summarized, big data is the large amount of data which exceeds the traditional database technologies (Vishnoi et. al, 2018) In addition, a fourth V, for vercity, is sometimes included in order to describe big data´s level of trustworthiness, truthfulness and meaningfulness (Gentsch, 2019). In other words, the credibility and representatives of the data collected.

2.1.2 Deep learning

Using artificial intelligence to gain market knowledge the same way as humans is performed through the concept of *deep learning*. Deep learning is a kind of machine learning that achieves great flexibility and power by including statistics and predictive modeling by learning to represent the world as a nested hierarchy of concepts and representations (concepts computed to relatively simpler concepts, representations computed less abstract).

(Burns & Brush, 2021) (LeCun et al., 2015) In practice, it can be viewed as a method for developing analytical AI for marketing decisions (Rust, 2019) , making the collecting and analyzing of large amounts of data faster and easier (Burns & Brush, 2021). For example, using big data, a deep learning method can be to estimate the prediction that is superior to previous regressions predictions in numerical marketing experiments (Chien et al., 2020).

2.1.3 Algorithms

Big data and machine learning relies on computer algorithms to create value for marketers. This is because machine learned algorithms make it possible to analyze the data collected, by learning the mathematical processes, rules or instructions to solve data problems or other calculations (LeCun et al., 2015: Mahesh, 2019).

Larger amounts of big data makes the use of algorithms essential in order to analyze and interpret the data in order to be provided value for future operational activities (Gentsch, 2019). Algorithms in marketing are mainly used for advertising, whereas for example Facebook algorithms are used to learn about their users´ preferences through their online behavior to distinguish and identify their interests (Rainie, 2019). Use of algorithms has a large impact on consumers´decision-making, and is therefore a central topic in this thesis (Kannan & Li, 2017).

2.2 Autonomy and consumer choice

Different disciplines have offered different definitions and constructs related to autonomy. One discipline that has thoroughly dealt with the concept of autonomy is philosophy, specifically as a part of a discussion about what it means and what is required for an agent to have free will. Some argue that free will is an agent's capacity to unimpededly choose between different courses of action (Omoregie, 2015) or an agent's ability to choose and do otherwise (Kane, 2011), while others suggest that free will is the capacity to make choices undetermined by past events (Baumeister & Monroe, 2014). As such, in the context of consumer behavior and consumer choice, exercising free will is akin to the definition of autonomy, specifically the "consumers' ability to make and enact decisions on their own" (Wertenbroch et al., 2020), without the influence of others. There is a distinction between autonomy and perceived control, where control more relates to the ability to influence outcomes through actions and choices, and autonomy relates to the "consumers' freedom in initiating behavior regardless of their ability to impact the outcome" (Skinner, 1996, as cited in Wertenbroch et al., 2020).

It is a marketers' job to identify the needs of their target audience and followingly provide the best solution for the consumer. However, there are also existing ethical concerns. Drumwright (2018) argues that general marketing can be deceptive, manipulative, intrusive, and wasteful (Drumwright, 2018, as cited Heath et al., 2018). Content or marketing that appears to originate from "digital publishers" but in reality is done by marketers also raises concerns about the fairness of marketing. This concept is called camouflaged marketing, where the advertisement is "camouflaged" in its surroundings, and appears as native content rather than as marketing. Such tactics could be perceived as unfair to the consumer, as the commercial aspect of the message is camouflaged within the content itself, and hence compromise the autonomy of the consumer. Similarly, "stealth marketing", where the consumer is unaware that they are the target of marketing, thus compromising the consumer autonomy in the same manner, as the advertisement is concealed from the consumer (Drumwright, 2018, as cited in Heath et al., 2018).

2.2.1 Actual vs perceived autonomy

Investigating consumer autonomy in this thesis, it is important to distinguish between *actual* and *perceived* autonomy. Actual autonomy refers to the degree to which an individual in practice (hence consumers) make and decide its own decisions independently - in this case purchase decisions. A person may not be aware of its actual level of autonomy, as such decisions often depend on automatic thought processes in the subconscious (Kahneman, 2011). This is the exact argument for separating the *autonomy* term, because perceived autonomy on the other hand, is the person's individual impression or perception of the degree of autonomy in decision making, based on the subjective and deliberate cognitive processes (Baumeister & Monroe, 2014). Furthermore, a person's actual autonomy. As technological developments introduce a bunch of new and improved marketing techniques (algorithms, targeting approaches etc.), consumers today are exposed to manipulations and external impacts in their decision making – more than they actually believe and perceive. With such marketing approaches, the degree of external influence on their decisions becomes “hidden” to the consumers (Wertenbroch et al., 2020). In comparison, as humans do not count their 12-13 breaths a minute and neither perceive this phenomena, the same may be argued to the degree of consumers actual autonomy, whereas the perceived autonomy may be lower than what is the actual reality. Future research suggests analyzing and specifying the gap between individuals´ between actual and perceived autonomy.

2.2.2 Benefits and costs of autonomy in consumer choice

This section will tackle the question of how a heightened sense of autonomy can affect choice and increase consumer well-being, in a context surpassing the basic need of autonomy in consumer choice.

Literature has shown that consumers find utility from positive self-attributions, specifically feeling in control of one’s choices attributes towards positive outcomes, and a heightened feeling of competence (Andre et al., 2017). According to Feather & Simon (1978, as cited in Andre et al., 2017), consumers have “been shown to feel a greater sense of responsibility for positive outcomes when the chain of causality linking their thoughts, actions, and the outcome is conspicuous”. For example, choosing the more morally good option (i.e., healthy vs unhealthy) requires self-control, and may lead to positive self-attributions as a result of a heightened sense of willpower and the ability to resist temptations (Dhar and Wertenbroch, 2012).

Reducing consumers’ belief in their own sense of autonomy also has a “variety of undesirable consequences such as reduced helpfulness and higher levels of aggression (Baumeister et al., 2009, cited in Andre et al, 2017) and a lowered sense of self-control in their choices.

According to Andre et al. (2017), if online consumers believe that the algorithms are getting “more and more persuasive and are predictive of their own preferences, it could provide them with a justification to indulge more following tempting ads”.

2.3 AI recommendation technology and the impact on consumer autonomy

What is clear from research is that product recommendation technology (AI: big data, machine learning, algorithms) influences consumer choices, and even manages to change consumers´ preferences (Franklin et al., 2022: Cha et al., 2019: Melumad et al., 2020: Murray & Haubl, 2009). As stated earlier, AI-based technology provides its benefits to some customers, but an overload of choices can be harmful to them. For example, a study showed that when people were offered 24 options versus 6 options, there were more purchases from the set with only 6 options (Andre et al., 2017). In addition, when consumers are aware of their choices being predicted based on their previous choices, a study showed that some actually decide to choose the less-preferred options in order to retain their sense of autonomy (Carmon et al., 2019). In brief, consumers who experience “too many” AI-based recommendations, can tend to become more confused and uncertain of their actual needs or purchase preferences. Furthermore, adding that the need for autonomous choices may be more important to retain ahead of choosing predictably (trade off), one could argue that AI recommendation systems may have a bad impact on consumer behavior, and also on future sales. Therefore, marketers should take consumer autonomy into account when implementing AI recommendation technology.

2.4 Privacy concerns and AI

In the emerging age of artificial intelligence & big data, especially within marketing and online websites, a concern to many is the large flows of personal information being collected by third party organizations (Stahl & Wright, 2018). Large amounts of personal information remains in organizations´ databases, which leaves a threat to customers if their information is exposed to other purposes or hacker attacks. (Mazurek & Malagocka, 2019)

From a study, 70% of the businesses revealed they have increased their personal data collection, whilst consumers (40%) at the same time claim they do not trust the brands to use their data. Another survey showed that 62% of its business leader respondents felt that they should do more to protect customer data (Whitney, 2021). In addition, as artificial intelligence evolves, the analysis of personal information to new levels of power and speed, likely to use the information that may intrude on privacy interests (Kerry, 2020). In other words, as the utilization of AI increases, this does also include a larger amount of data to be abused when it comes to privacy. A report also showed that personal customer data (name, email and password) was the most common type of data exposed, by 44% (IBM, 2021). The assumption of AI to be a threat to customer´s privacy is present for many. The modern digital age has experienced several leaks of personal identifiable information (PII) for millions of users, where people´s data has been lost, stolen, hacked and exposed (IBM, 2021).

2.5 Hofstede’s cultural dimensions

2.5.1 Power distance

The degree of inequality a member accepts and expects in organizations and institutions. Small power distance suggests the use of power should be legitimate and is subject to criteria of good and evil, while a larger level indicates power, and its legitimacy is more or less irrelevant (Hofstede, 2011).

2.5.2 Individualism

Opposite to each other, describes the degree to which people in a society are (and prefer) being integrated into groups. Individualistic cultures look more after themselves individually and their immediate family, while collectivistic cultures emphasize groups and extended families with a level of unquestioning loyalty and protection of their strong, cohesive groups (Hofstede, 2011).

2.5.3 Masculinity

Opposite to each other as well, this dimension refers to the value distribution between genders that are more important in a society, whereas masculine cultures often have preferences for assertiveness, competition and social role differentiation between genders in society, whilst feminine cultures prefer cooperation, modesty and less social role differentiation between genders and. In masculine cultures, men should be and women may be assertive and ambitious, while feminine cultures prefer that both men and women should be modest and caring (Hofstede, 2011).

2.5.4 Uncertainty avoidance

Refers to the extent an individual in a society tolerates uncertainty. It indicates the extent a culture member feels uncertain or uncomfortable in unforeseen and unexpected situations. Culture with low levels of this dimensions accepts uncertainty and takes each day as it comes, while high-level cultures see occasions in life as continuous threats that must be fought and accounted for (Hofstede, 2011).

2.5.5 Long term vs short term orientation

Cultures emphasizing long-term orientation prefer preparing for the future and thus where the most important events in life will occur. Such cultures focus on persistence and adapts to circumstances. Short-term orientation, on the other hand, are past and present time-oriented and have a higher level of personal steadiness and stability, respecting traditions and social obligations (Hofstede, 2011).

2.5.6 Indulgence vs restraint

Has a weakly negative correlation to the dimensions above. Indulgent cultures, weak control, involve societies that allow relatively free gratification and human desires to enjoy life and having fun, while restrained cultures suppress gratification of needs and have more strict social norms and a perception of helplessness. The latter is relatively less happy in general (Hofstede, 2011).

2.6 Hofstede’s cultural dimensions and consumer autonomy

2.6.1 Power distance and consumer autonomy

The degree of cultural power distance (PD) does to a very small extent provide information about its relationship to *consumer autonomy*. Basabe (2005) shows a negative correlation between Hofstede´s (2001) power distance dimension and the autonomy theory by Schwartz (1994). The higher degree of power distance may indicate a smaller need for autonomy in cultures. This is supported by Lee & Antonakis (2012) & Conway et al. (1992) who suggest that low-PD societies prefer to make their own choices and the need for autonomy is a cultural norm they value in order to reach satisfaction of having the right to decide and act independently. In addition, Hofstede et al. (2011) claims cultures with small power distance emphasize autonomy as a preserving need. At the same time, high-PD cultures tend to have a larger acceptance and tolerance for lacking autonomy and may even prefer activities under conditions where they have reduced autonomy and power. Individuals in these societies may also perform even better under such circumstances and be satisfied despite their autonomy not present (Eylon & Au, 1999). This theoretical foundation suggests that the lower the level of power distance, the higher is the need for autonomy.

H_1: A higher level of power distance contributes to lower consumer autonomy.

2.6.2 Individualism and consumer autonomy

Individualism in cultures is arguably, along with power distance, the dimension that is researched the most in conjunction with autonomy. Common is that individualistic people tend to make autonomous decisions and have a relation to autonomy and self-orientation (Triandis & Gelfand, 2012). This involves individualistic cultures to prefer a private life and self-determination, because they are less concerned by taking joint decision-making with others, thus are more likely to have a higher extent of autonomy when deciding (Wagner, 1995). Proportionally, but on the other hand, collectivistic cultures do not necessarily have a strong value for autonomy, with individuals having a low preference for the term and most decisions are taken with influence from others (Capece et at., 2013). In addition, collectivistic individuals do not feel a lack of value if autonomy is not present, and therefore have a higher tolerance for absence of autonomy in decision making (Chen et al., 2013). Markus & Kitayama (2010) argue that collective self-construal cultures tend to be more satisfied when choices are made behalf of themselves by other in-group members. This could be linked to a consumer context, whereas collectivistic individuals accept to a larger extent to be influenced by "others" (ex. recommendations) when deciding.

Based on this theory, it is suggested that the higher level of individualism, the higher is the level of autonomous choices in a consumer context.

H_2: A higher level of individualism contributes to higher consumer autonomy

2.6.3 Masculinity and consumer autonomy

A masculine culture values materialism and prefers to have more than others (Ger & Belk, 1996: Ogden & Cheng 2011). In addition, materialistic "masculine" people often search relatively more for the source of happiness and success and personal well-being in life (Wang et al., 2017: Richins and Dawson 1992) Furthermore, materialism influences personal well-being through the three basic psychological needs: autonomy, competence and relatedness. Research has shown that autonomy reduces well-being due to a low satisfaction by the psychological need for autonomy only (Ditmar et al., 2014: Nagpaul & Pang, 2016: Wang et al., 2017). Therefore, perceiving that activities are endorsed by or congruent with one's integrated sense of self (Deci & Ryan, 2014), i.e. perceived autonomy does arguably not contribute to a higher need for autonomy in high masculine societies in which the high extent of materialism causes a lower satisfaction of autonomy to individuals. This is also supported by the self-determination theory (STD) which claims that the three psychological needs should be satisfied in order to experience well-being and happiness (Deci & Ryan, 2008: Wang et al., 2017: Niemiec & Ryan, 2009). Summarized, one can argue that high masculine cultures that highly value materialism through chasing success and happiness in life, do not prefer to have autonomy as a need - as this reduces their satisfaction. Therefore, it is suggested that high masculine-societies perceive themselves as individuals who do not prefer autonomy.

H_3: A higher level of masculinity contributes to lower consumer autonomy

2.6.4 Uncertainty avoidance and consumer autonomy

When searching for the link between uncertainty avoidance and autonomy, literature provides more or less no theoretical or empirical results. One finding was that there are negative (-0.35) and positive (0.43) correlation between both affective and intellectual autonomy with respect to uncertainty avoidance (Glazer, 2021). Moreover, as people in cultures scoring high on uncertainty avoidance tend to be more alien to new things and situations (Tellis et al., 2003), one can argue that such societies prefer a higher degree of autonomy to possess a larger self-control of their “uncertain” dilemmas. On the other hand, consumers may also wish to reduce their level of uncertainty in decision-making if they have trustful supporting tools for personal structure (Möller & Eisend, 2010). Therefore, (high) UA can either be argued as a dimension that prefers more autonomy through a high sense of self-control around what’s new and uncertain. On the other hand, as discussed, an individual with high UA may also wish for help and rules around “what´s new and uncertain”, if external influence or support is more preferred to reduce uncertainty. This first argument is supported by Boyadzhieva (2016) who claims that “The degree of uncertainty and autonomy are inversely proportional meaning that the higher the uncertainty, the lower the autonomy and vice versa” (Boyadzhieva, 2016). In addition, Murray & Schlacter (1990) suggest that consumer cultures that aim to avoid uncertainty will be more cautious when making their own decisions. This may speak for a preference for giving away autonomy in return for external advice in decision making, to be consulted and avoid uncertainty.

H_4: A higher level of uncertainty avoidance contributes to lower consumer autonomy

3. Laws and regulations

3.1 GDPR

General Data Protection Regulation (GDPR) is a security law by the European Union (EU) with the purpose to protect the processing of personal data and the movement of such data of individuals online. The regulation aims to strengthen their fundamental rights and facilitate public business behavior as well, by clarifying protective rules (EU, 2022). As the likes of big data information and algorithmic profiling historically have experienced critique for their collecting of personal user information in marketing, the GDPR is established to avoid such coincidences. Companies in member countries of the EU who collect data against the GDPR compliance are punished with administrative, regulatory and financial sanctions by the organization (Voss & Bouthin-Dumas, 2021). A famous incident from 2013, by the United States´ Senate Report, where information from the broking industry by data brokers lacked transparency in their targeting of user weaknesses, by categorizing them such as “Rural and Barely Making it” or “Credit crunched: City Families, before selling these categorizations as targeting marketing for bank. These categorizations was seen discriminatory by many, and also unethical marketing by the banks as they offered the vulnerable categorizations short loans with high-interest rate (Padden & Ojehag-Petterson, 2021: Jonas & Hiller, 2021). Despite this occurring in the US, it explains an example of businesses using personal information for other purposes, without consumers consent (or awareness) – which GDPR aims to eliminate.

4. Methodology

This section will cover the entire process on how the thesis data is created, conducted, and analyzed. The section will first explain the research design, followed by how data was collected and analyzed. Lastly, the validity of the data will be tested, and a description of each variable and analysis is given.

4.1 Research design

As the purpose for the thesis is to identify how culture influences consumer autonomy, a quantitative research approach was used. A quantitative research involves a set of statistical or numerical data, investigating trends, social phenomena and relationships between variables in order to test and provide answers to hypotheses (Watson, 2015).. A quantitative research approach can explore numeric patterns of a set of variables through a questionnaire, structured observations or experiments (Ahmad et al., 2019). For large sample sizes, a quantitative approach is a good fit as it manages to represent data findings from a specific population. Being capable of dealing with several numbers to assess information, it provides accurate and reliable results that can be compared and generalized (Goertzen, 2017). As our questionnaire and adaptive conjoint analysis target one population only, these are two appropriate and effective strategies for measuring how the cultural dimensions within Norway influence consumer autonomy.

4.1.1 Survey structure

1. Hofstede's six cultural dimensions: 24 items + 6 demographic items
2. Perceived autonomy: 12 items
3. Privacy concern: 5 items
4. ACA autonomy: 3 items
5. ACA privacy: 3 items

In order to measure the importance of autonomy and privacy, the adaptive conjoint analysis also measured the importance of price, discount and preference for AI in relation to the two former factors. This made it possible to identify how important the several factors were in relation to each other, by adding the additional factors into the conjoint in order to analyze the respondents´ selection pattern. For example, autonomy might be affected by a respondent who is against use of AI, or who is easily willing to give up autonomy for a larger discount or price. Therefore, it was important for the main study to implement the additional measurements to measure the respondents‘ relative emphasis on autonomy. e.

Additional measurements:

1. Price: 3 items (ACA)
2. Discount: 3 items (ACA)
3. Preference for artificial intelligence: 2 items (ACA)

Total: 58 items

4.1.2 Experimental design: the Adaptive Conjoint Analysis

The adaptive conjoint analysis (ACA) is a rating-based conjoint analysis approach that measures respondent´s preferences and their relative importance of different attributes (specified). This information is used to estimate how meaningful selected concepts are in relation to each other, and to which extent a concept attribute is weighted for the decision-making in adapted choice scenarios. In brief, a conjoint analysis measures the tradeoffs between attributes (Eggers et al., 2022). In the Sawtooth Software, the ACA system allows up to 30 attributes involving 15 levels for each. The software focuses on the most relevant attributes for an analysis, and focuses on just a few attributes at a time to avoid information overload (Sawtooth, 2022). Often used to analyze consumer preferences, the ACA in Sawtooth was a very appropriate tool to investigate how much consumer autonomy and privacy concerns are important to the respondents (as consumers) relative to other attributes.. Finally, Sawtooth provided a percentage to the extent of how much each attribute decided or impacted the respondents' ratings, both in the "what if" and the regular scenarios that was conducted in the analysis.

4.2 Data collection

4.2.1 Sawtooth

Sawtooth software was the program used for collecting data from surveys. The survey was split into two parts. Part 1 consisted of the adaptive conjoint analysis, while part 2 of the questionnaire. The front page had information about the survey´s purpose and that two students from the NTNU Ålesund were behind it. In addition, the respondents were assured that no personal or online information about them would be collected. The gathering of IP-addresses in Sawtooth was also turned off. Therefore, the survey was completely anonymous. Furthermore, the software performed the ACA randomly arranged for the various variables' conditions, thus minimizing the chance of random errors in the data sample. Finally, after all answers were collected, the variables were transferred into SPSS.

4.2.2 SPSS

All of the statistical analysis and measurements are performed using the Statistical Package for the Social Sciences, famously known as SPSS. In brief, SPSS is used to interpret and test the results of research (Arkkelin, 2014). The entire set of information from the 104 respondents was imported to SPSS from the Sawtooth software. Here, several variables were computed into new variables in order to measure and analyze the various purposes for this thesis. All the figures and tables in this text and it´s appendix are retrieved from SPSS

4.2.4 Pilot study

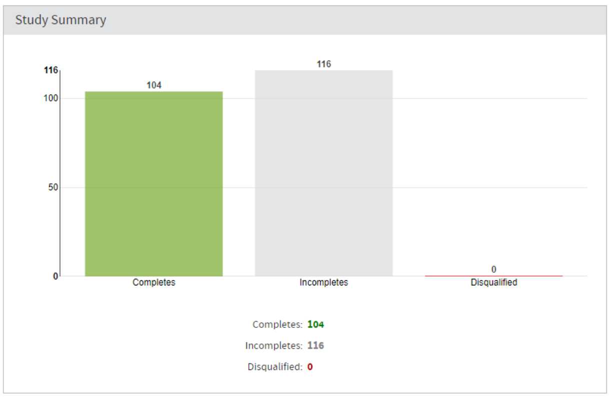
Before publishing the survey to the public population, a pilot study was shared between family and close friends. This was done to receive feedback from the audience in order to make necessary changes or improvements to the survey. Simultaneously, this gave insight into how the Sawtooth software would function for the analysis, as this was our first time using the program.

The pilot study consisted of 17 respondents, of which everyone completed the whole survey. Mostly, the feedback was very positive. However, a small issue to some respondents concerned the survey´s time duration, claimed to be a bit long. Therefore, the text was gone over again to cut down a few bits. Despite this, the survey lasted approximately 12 minutes, which was still relatively long to many participants (see Incomplete descriptives in “Main study”). In addition, a few formulations for certain questions were edited, based on feedback.

4.2.5 Main study

After changes were made, the survey was completed and ready to be published. As the target group was the Norwegian population, the survey was only shared with friends on Facebook. This was done by sharing the survey link on each other´ s Facebook wall and through personal direct messages. Since only 100+ respondents were needed, this was considered this was the most effective method to reach into family, friends and acquaintances, as previous experience has proved that groups of strangers are generally very little willing to complete surveys for others´. Therefore, sharing this was considered as the most effective way to reach out to a Norwegian population and to receive the needed number of respondents.

Eventually, after over one and a half weeks, a total of 104 had completed the entire survey. A relatively long waiting time, but at the same time expected according to the schedule as the survey was relatively large and time consuming to complete. Statistics below support this assumption in which a huge number of participants did not complete the survey after launch. A total of 116 participants did not finish, whereas the introduction part explaining the survey scenario was a weak-point with almost 30 percent abandoning after this point. All incompletes were removed to ensure a reliable sample.



Incompletes Report

Last Question Seen	Incompletes	% of Respondents
Intro	62	28%
DEL1	11	5%
ACA_Rating1	31	14%
ACA_Importance1	1	0%
ACA_Pair1	1	0%
ACA_Pair3	2	0%
ACA_Pair4	4	1%
ACA_Pair6	1	0%
Info1	1	0%
SLUTT	2	0%

4.3 Description of variables

This study contains several variables that are collected in order to discover the relationship between consumer preferences & behavior and culture. There are only four main variables that are taking part in testing the correlations relative to Hofstede's six culture variable indexes, in order to answer the hypotheses introduced earlier in this paper. The selected variables will provide information about respondents':

1) autonomy and privacy importance, through the conjoint analysis

2) how they perceive their consumer autonomy and privacy concern, based on survey results

Based on this, the four selected variables are 1) ACA autonomy, 2) ACA privacy, 3) perceived autonomy and 4) privacy concerns. These will be described below.

4.3.1 ACA autonomy

Three different levels of autonomy was given to the respondents, in which they firstly were asked about their significance of being able to choose freely, by ranking three different conditions. Thereafter, in a randomly assigned conjoint analysis they were asked to select a combination with the most preferred insurance deal, consisting of other additional variable terms. By this, one is able to measure to what extent being able to choose freely (autonomy) was important to the respondents, as well as how much the importance contributed in choosing the preferable insurance package.

In the low level of autonomy, the respondents were asked to rank their preference of accepting "The car loan requires you to pick their recommended car insurance company". The medium level was: "You choose freely between 5 different car insurance companies", while the high level was: "You choose freely which car insurance company you want". Firstly, these conditions were asked to be ranked separately to each other on a Likert scale 1-7 from "Not desirable" to" Extremely desirable" (see appendix Y) Secondly, the importance of choosing one condition above another was to be selected. Thirdly, when selecting their preferred insurance package, the conditions were in random combinations with other variables, i.e., against each other.

Therefore, as the experiment managed to test the respondents by creating variations and combinations that impacted the respondents' actual preferences regarding autonomy, the "ACA Autonomy" variable was allowed to be conducted.

4.3.2 ACA privacy

Same procedure, where three different levels of privacy information, given to the insurance company, were ranked from 1-7 on Likert scale from "Not Desirable" to ``Extremely desirable". A low level of privacy means a person is willing to give away relatively much information, and vice versa.

As from the ACA autonomy application, the variable is measured by the Likert scale, then by the importance of giving up one level of information versus another and finally how a certain privacy level impacts the decision when choosing an insurance package. Eventually, the data results computes the variable for "ACA privacy".

The three conditions are presented in appendix Y.

4.3.3 Perceived autonomy

The questions for the measurement of perceived autonomy were adapted from Chen et al. (2014) and Michaelsen et al. 2021), as cited in Haugstulen (2021). This variable is measured on the basis of 12 items (see appendix Y), using a Likert scale 1-7 from "Strongly agree" to "Strongly disagree". A low scale score on the "agree side" for question 5 to 8 means a low level of perceived autonomy, as these questions are negatively loaded from an autonomy perspective. However, low scale scores on the "agree side" for question 1-4 and 9-12 will indicate a high level of perceived autonomy, on the other hand. Therefore, the scale scores for these questions were reversed in the data sample to show the same impact on the perceived autonomy variable from all 12 questions, i.e., the higher Likert scale in the data results, the more perceived autonomy.

4.3.4 Privacy concerns

The purpose of this variable is to measure the sample´s privacy concern in terms of giving up personal information to insurance companies. The five survey questions (see appendix Y) concerns to what extent on a Likert scale 1-7 the respondents are concerned about the likes of their online personal privacy information, financial information, personal data being used for other purposes, online behavior on websites being tracked and the threat of personal information being shared to other parties. The questions are basically measured from 1 (Very concerned) to 7 (Very unconcerned). However, these data are also reversed into the variable, meaning that the higher scale score, the higher is the concern.

4.4 Description of analyses

4.4.1 Descriptives

Demographic information was included in the study, first of all to control that all respondents are Norwegian internationals. Choosing Norway as their nation on a scale of 1-196, would result in a value of 131, which was selected by all 104 respondents. This is the control variable for the survey, as it secures the data to consist of the selected population only (Pallant, 2016). In addition, the respondents were asked about their style of gender and age group. Gender was measured on a scale 1-3, whereas as 1 = Male, 2 = Female and 3 = Do not specify. The various age groups was measured on a scale 1-8 with indicator 1 “for Under 20”, 2 for “20-24”, 3 for “25-29”, 4 for “30-34”, 5 for “35-39”, 6 for “40-49”, 7 for “50-59 and 8 for “60 or over.

4.4.1 Tests of normality

To make sure the distribution of scores on a dependent variable is “normal”, tests of normality were conducted. This test obtains a Kolmogorov-Smirnov statistic to assess normality of the distribution of scores. A non-significant result with a Sig. value above .05 indicates normality (Pallant, 2016). As research often contains dependent variable scores that are not normally distributed, it is important to check the data distribution of scores. The skewness score provides information about the distribution´s symmetry, together with the kurtosis which gives information about the distribution’s “peakedness” (Pallant, 2016). A perfectly normal distribution is present if both values are equal to 0, but this is rather uncommon. However, a positive skewness value indicates the scores are clustered to the left at the low values, while a negative value will show a clustering of scores in the top right-hand side of a graph (Pallant, 2016). A positive kurtosis score means the distribution is rather peaked in a center cluster, while a negative score indicates a relatively flat distribution. In addition, a histogram was also used to provide a graphical examination of various variables, to see which side the variables are skewed to.

Sig. values less than .05 are quite common in larger samples, despite suggesting violation of the normality assumptions. Same applies to scales and measures that are skewed either positively or negatively. However, such non-normal distribution does not necessarily indicate a problem with the scale, but rather occurs in social science due to the underlying nature of the construct being measured (Pallant, 2016).

4.4.2 Reliability analysis

Testing the sample for reliability is important to check how free it is from random error. It is a type of correlation test with itself (Haugstulen, 2021). This can be measured through internal consistency, which indicates the items´ degree of how they "hang together" and if they measure the same underlying construct. The common indicator used of internal consistency is the Cronbach's alpha coefficient. This indicator (from 0 to 1) should preferably be above .7 to indicate internal consistency and a good reliability of the scale (Pallant, 2016). Short scales will often find quite low Cronbach values (ex. .5), as these values are quite sensitive to the number of items in the scale. Therefore, it might be appropriate to report the inter-item correlation for low scale items (Pallant, 2016).

4.4.3 Correlation analysis

In short words, a correlation analysis provides a description of the linear relationships between two variables. It gives insight about their strength and direction in relation to each other (Pallant, 2016). SPSS is able to calculate two types of correlations; a simple bivariate correlation analysis between two variables, and a partial correlation, which explores the relationship between two variables while controlling for another variable (Pallant, 2016). As this thesis speculates in the relationships between two variables, the bivariate correlation was used. Here, the indicators Pearson correlation coefficients (r) and non-parametric Spearman rho tell whether there is a positive or negative correlation between the variables, by respectively positive and negative values. Positive correlation means if a variable increases, the other does too, while a negative correlation means a variable increases, the other decreases. A perfect correlation of 1 or -1 means that one can determine exactly one of the variable´s values by knowing the value of the other. This relationship can be shown in a scatterplot that contains a straight line. A nonexistent relationship between two variables is present with a value of 0. (Pallant, 2016). This is the main type of analysis for the thesis, because this will give answers to the hypotheses through indicating potential relationships between the main variables.

4.4.4 Linear regression

A simple linear regression was performed to estimate the relationship between the dependent (perceived autonomy) and independent variables (PD, IDV, MAS, UA, LTO and IVR). In addition the privacy concerns variable was also tested as a dependent variable. .Generally, in a linear regression the dependent variable is a constant value and is labeled as a regression coefficient or regression weight. The independent variable is called as a predictor of the dependent value, i.e., linear regression is a predictive analysis of a variable´s outcome (Lunt, 2013). At the same time, the analysis provides an extension of correlation of which direction the linear relationship between the predictor and dependent variable moves in relation to each other. However, in contrast to a correlation analysis, the linear regression provides a prediction of how the explanatory (dependent) variables cause a change in the response (independent) variable, through a statistical model (Kumari & Yadav, 2018). Finally, the analysis requires six assumptions to be valid:

1. There exist a linear relationship between the dependent (Y) and independent (X) variables

2. Any value of Y possess the same variance of residual (homoscedasticity)

3. X is measured without any experimental error

4. Any fixed value of X includes normal distribution for Y

5. All Y values are independent from each other, but depend on X

6. The values of X are set by the researcher

(Kumari & Yada, 2018) (Devassy & George, 2021)

5. Results

5.1 Descriptives

The questions from each of the survey pages were mandatory to complete before moving on to the next, i.e., all incomplete results were removed from the dataset. This resulted in a total of 104 respondents, illustrated in Appendix A.

5.1.1 Demographics

The frequency analysis (Appendix A) shows a gender dispersion of 56 males (53.8 percent), 45 females (43.3 percent), while 3 respondents answered that they would not specify their gender (2.9 percent).

The most frequent age groups of the respondents were “20-24” and “25-29”, respectively at 22 and 23 respondents. As Facebook was used to share the survey, it can be argued that this is a natural occurrence, considering that peers are the most frequent (friends and family). Age groups “40-49” and “50-59” (respectively 17 and 12 respondents) were also quite frequent.

Lastly, all of the respondents live in Norway, as this was the targeted population of the survey.

5.1.2 Perceived autonomy

The 104 respondents answered all the 12 questions spreading across the entire range, illustrated as minimum and maximum in Appendix B. The respondents additionally answered on average a mean value above 4 (more specifically from 4.36 to 5.56), which is on the higher side of scale.

The “PerceivedAutonomy” scale was computed from the 12 survey questions. Out of the 104 respondents, the minimum value was 2.67 and the maximum value was computed to 7, where the latter is at the maximum range of the Likert scale.

The mean value was calculated to 5.13, indicating that the average respondent feels they have a higher degree of autonomy.

A measurement of skewness was also included in the descriptive analysis. The skewness value is an indication of how the scores of the questions/scales are distributed, or the *symmetry* of the distribution. A positive skewness value indicates that the scores are clustered more towards the low values, while a negative skewness value indicates that scores are clustered towards the high values (Pallant, 2016). From Appendix B, the skewness values for each individual question, as well as the summated scale, are negative, indicating that the scores are clustered to the right at the high values.

5.1.3 Privacy concerns

Similarly to the Perceived autonomy questions, all five questions were answered across the entire range, displayed as minimum and maximum values in Appendix C. The average mean of each individual question ranged from 4.88 to 5.20, which is on the high side of the Likert scale.

Similarly, the "PerceivedPrivacy" scale was computed from five questions, and out of 104 respondents, the minimum value was at the lowest possible value of 1 and the maximum value was at the highest possible value of 7.

The mean value was then calculated to 5.05, indicating that the average respondent is on the higher side of the scale when it comes to concerns about their privacy.

The skewness values for all the questions and the summated scales are negative, indicating a clustering to the right at the high values.

5.1.4 Assessing normality

To assess the normality of the variables displayed in table 1, the Kolmogorov-Smirnov statistic will be assessed in addition to interpreting the results from the histograms for each variable. The Kolmogorov-Smirnov statistics and the histograms will assess the normality of the variables by looking at the distribution of scores. A significant result with a Sig. value of less than .05 suggests a violation of the assumption of normality, where a non-significant result (above .05) indicates normality (Pallant, 2016). Furthermore, the Kolmogorov-Smirnov statistics will be interpreted for all variables. For the interpretation of the histograms, “Gender”, “AgeGroup” and “Country” will be excluded as these variables were thoroughly interpreted in section 5.1.1.

Notably, variables “PerceivedAutonomy” and “PerceivedPrivacy” used a 7-point Likert scale, whereas the cultural dimensions “PowerDistance”, “Individualism”, “Masculinity”, “UncertaintyAvoidance”, “LongTermOrientation” and “Indulgence” used a 5-point Likert scale. This is important information to consider when looking at the distributions in the histograms.

From the results of the analysis found in table 1, the Sig. value for all variables is .000. The exception is “PerceivedPrivacy”, where the Sig. value is .001. Nonetheless, all Sig. values are below the .05 limit, which suggests a violation of the assumption of normality. Due to the fact that many scales and measures, often the ones in social sciences, have skewed scores (Pallant, 2016). This may not indicate a fault with the scales, but rather “reflects the underlying nature of the construct being measured” (Pallant, 2016, p. 81). On the basis of this, the data analysis could continue without further action.

Tests of Normality

	Kolmogorov-Smirnov		
	Statistic	df	Sig.
PerceivedAutonomy	.130	104	.000
PrivacyConcerns	.118	104	.001
PowerDistance	.126	104	.000
Individualism	.161	104	.000
Masculinity	.157	104	.000
UncertaintyAvoidance	.181	104	.000
LongTermOrientation	.136	104	.000
Indulgence	.173	104	.000
Gender	.349	104	.000
AgeGroup	.209	104	.000
Country	.	104	.

Table 1: Tests of Normality

5.1.5 Adaptive Conjoint Analysis

Descriptive statistics were performed for the ACA variables. From the mean scores, measuring the percentage of the importance, the highest value is 25.3 for the “Discount” variable, followed by “Price” at 23.4. This was expected as the total payment often is decisive when purchasing insurance. More interestingly, autonomy and privacy, respectively at 20.4 and 20.9, was also important to the respondents. Both items accounted for almost 21% of the respondents´ answers, where the range was very large. Some emphasize their answers a lot about autonomy (max.41.1%) and privacy (max.39.3%), in which others did not consider the two terms at all, more or less, respectively a minimum value of 2.3 and 2. The preference for using AI to calculate future insurance settlements was least important to the respondents, only with a contribution averaging at 10% in their decision-making.

5.2 Reliability

In order to be able to analyze, interpret and compare scales in a study, it is important that the scales that one uses are reliable. While there are several aspects to the concept reliability, measuring the scale’s internal consistency is one of the more frequently used methods. This is measured by the Cronbach’s Alpha coefficient, which measures whether or not, in this case, the questions are measuring the same construct (Pallant, 2016). The Cronbach’s Alpha should preferably be above .7. For smaller scales containing less than 10 items it is quite common to find lower Cronbach’s Alpha values, where .5 would be considered to be the accepted minimum. However, in such cases, it would be more appropriate to look at the mean inter-item correlation value (DeVellis, 2012, as cited in Pallant, 2016). Here, the items mean inter-item correlation value should be between .15 and .5 (Clark & Watson, 1995).

Table 2 (below) shows a summary of all Cronbach’s Alpha calculated in SPSS, which were summarized from the outputs in Appendix F-M.

	Cronbach’s Alpha
Perceived autonomy	0.872
Privacy concerns	0.891
Power distance	0.165
Individualism	0.671
Masculinity	0.729
Uncertainty avoidance	0.360
Long term orientation	0.553
Indulgence	0.269

Table 2: Cronbach’s Alpha

From table 2, analyses find that “Perceived autonomy”, “Privacy concerns” and “Masculinity” are the only scales above .7, as was the recommended minimum by DeVellis (2012). For the remaining scales “Power distance”, “Individualism”, “Uncertainty avoidance”, “Long term orientation” and “Indulgence”, the Cronbach’ Alpha coefficients are below the recommended level. However, as stated above, in scales where the number of items are low, the Cronbach’s Alpha is often found to be quite low. This is the case for the mentioned scales, where all scales only contain four items each. Therefore, for these cases, the mean inter-item correlation will be considered.

5.2.1 Reliability of Perceived Autonomy

A reliability test (Appendix F) was conducted for the 12 questions/items concerning perceived autonomy (see Appendix Y).

The Cronbach’s Alpha coefficient for perceived autonomy was calculated to .872, which suggests very good internal consistency between the items. While values above .7 are acceptable, values above .8 are preferable (Pallant, 2016). In the Item-Total Statistics, it is shown that the Cronbach’s Alpha will increase to .882 if item 5 is deleted. However, considering that the Cronbach’s Alpha is already at a satisfactory level above .8 and that the Cronbach’s Alpha will only increase minimally by .01, the item will not be deleted from the scale.

5.2.2 Reliability of Privacy Concerns

The reliability test for privacy concerns (Appendix G) included 5 questions/items in its scale (Appendix Y).

The Cronbach’s Alpha coefficient for privacy concerns was calculated to .891, which suggests very good internal consistency and that they measure the same underlying characteristics (Pallant, 2016). The coefficient is at a *preferable* value (above .8). The Item-total statistics shows that no difference to the Cronbach’s Alpha will occur when any of the items are deleted.

5.2.3 Reliability of Power Distance

The reliability test for power distance (Appendix H) was conducted for a scale containing 4 questions/items (Appendix Y).

The Reliability Statistics output shows a low Cronbach's Alpha at .165, suggesting that the internal consistency is poor. Considering the nature of the scale where the number of items is low, it would be more beneficial here to mean inter-item correlations value. In the Summary Item Statistics, the mean value of inter-item correlations is calculated to .048, meaning below the recommended scale between .15 and .5. This suggests that the internal consistency is still poor. The Item-Total Statistics shows that the Cronbach's Alpha will increase to .253 if item 3 is deleted.

Running a new reliability test with item 3 removed (Appendix N), the Summary Item Statistics still shows that the mean value of inter-item correlations is low at .112. Again the Item-Total Statistics shows that if "HofQ23" (which is Hofstede's 23th question shown in Appendix Y) is removed, the Cronbach's Alpha will increase to .287. Yet again running a new test with items 3 and 4 removed (Appendix O), the Summary Item Statistics shows a satisfactory mean value of inter-item correlations at .172, indicating that removing items 3 and 4 result in acceptable internal consistency.

Removing too many items from the scale can also affect future results, and must also be taken into account when considering removing too many items from a scale. In this case, removing two items from the scale would leave only two items left in the scale. Considering that the corrected item-total correlation (Item-Total Statistics in Appendix H) shows negative value for item 3, which gives good cause to remove this item.

A new scale was created by removing item 3, but it should be noted that the internal consistency and reliability of this scale is questionable.

5.2.4 Reliability of Individualism

The reliability of Individualism (Appendix I) was conducted by testing a scale of 4 questions/items (Appendix Y).

The Cronbach's Alpha coefficient found in Reliability Statistics was calculated to .671, which initially suggests that the value is below the recommended level of .7. Scanning through Item-Total Statistics, it is found that the Cronbach's Alpha will not increase if any items are deleted.

However, since the scale has below 10 items, the recommended level is at .5, and thus, it can be argued that the scale shows good internal consistency. It would still be beneficial due to the small number of items in the scale to look at the mean inter-item correlations value in Summary Item Statistics. This value is .339, which is within the range between .15 and .5. Therefore, the Individualism scale shows good internal consistency.

5.2.5 Reliability of Masculinity

The reliability test of Masculinity (Appendix J) was conducted by testing a scale with 4 questions/items (Appendix Y).

SPSS calculates the Cronbach's Alpha to .729, as shown in Reliability Statistics. This suggests that the scale has a good internal consistency and that the items measure the same construct. The Item-Total Statistics shows that the Cronbach's Alpha coefficient cannot be increased if any of the items is deleted.

5.2.6 Reliability of Uncertainty Avoidance

The reliability test of uncertainty avoidance (Appendix K) was conducted on a scale containing 4 questions/items (Appendix Y).

In Reliability Statistics it is found that the Cronbach's Alpha coefficient is .360, which is below .7 and below the minimum for smaller scales (.5). The mean inter-item correlations value (Summary Item Statistics) is .120, which is below the recommended range between .15

and .5. However, it is found in Item-Total Statistics that the Cronbach's Alpha can be increased by deleting an item, specifically item 4.

Running a new reliability analysis without item 4 (Appendix P), the Cronbach's Alpha will increase to .397, meaning still below recommended values. However, the mean inter-item correlations value is now at .179, which is within the range of .15 and .5. Scanning the Item-Total Statistics output, it is found that the Cronbach's Alpha can be increased by deleting item 1. This is not done, due to the fact that the mean inter-item correlations value is acceptable.

To ensure reliability of the future tests, item 4 is removed and a new scale for Uncertainty avoidance is made.

5.2.7 Reliability of Long Term Orientation

The reliability test of long term orientation (Appendix L) was conducted by a 4-item scale (Appendix Y).

The Cronbach's Alpha value (Reliability Statistics) is calculated to .553, which is above the recommended minimum .5 for smaller scales. As the value is still below the initial .7 minimum, the mean inter-item correlations will be looked at. This value, found in Summary Item Statistics, is at .250, which is well within the recommended scale between .15 and .5.

In Item-Total Statistics, it is found that the Cronbach's Alpha coefficient can be increased by deleting item 2, but considering that the internal consistency of the scale is proven good in Summary Item Statistics, a new test will not be conducted.

5.2.8 Reliability of Indulgence

The reliability test of indulgence (Appendix M) was conducted on a scale of 4 questions/items (Appendix Y).

The Cronbach's Alpha reported from Reliability Statistics is at .269, while the mean inter-item correlations value (Summary Item Statistics) is .087. Both suggest very poor internal consistency of the scale. In Item-Total Statistics, however, it is found that item 4 can be deleted to improve the Cronbach's.

Running a new reliability test without item 4 (Appendix Q), the new Cronbach's Alpha value is at .354, but the mean inter-item correlations value is now at an acceptable level at .16. Item-Total Statistics shows that yet another item can be deleted to improve Cronbach's Alpha, but since the mean inter-item correlations already is acceptable, this is chosen to not do.

To make sure that the internal consistency of the scale is acceptable, item 4 is deleted from the scale.

5.3 Regression

To answer the hypotheses, linear regression analyses were conducted. As the hypotheses ask how each cultural dimension affects autonomy, and not how each cultural dimension interacts with each other to predict autonomy. Therefore, several simple linear regression analyses were conducted instead of multiple regression. Perceived autonomy and Privacy concerns as dependent variables are tested on each of the cultural dimensions.

5.3.1 Regression of Perceived Autonomy

Checking assumptions

The first step in a linear regression analysis is to check if the data used are actually suitable for linear regression. This is done by checking the assumptions specified in section 4.4.4.

All the assumptions can be tested by looking at Normal P-P Plot of Regression Standardized Residual and Scatterplot, both found in Appendix R.

In the Normal P-P Plot, the points should lie in a reasonably straight diagonal line from bottom left to top right (Pallant, 2016). As shown in Appendix R, all values in the Normal P-P Plots do lie in a reasonably straight diagonal line, suggesting no major deviations from normality.

In the Scatterplot, the values should have a reasonably rectangular distribution and the scores should mostly be clustered in the center, i.e, around 0 (Pallant, 2016). All Scatterplots in Appendix R show roughly a rectangular distribution and the scores are concentrated in the center. This suggests that the data shows homoscedasticity.

Checking for outliers is also important when conducting a regression analysis. Outliers are defined as cases that have standardized residuals, either below -3.3 or above 3.3 (Tabachnick & Fidell, 2013, as cited in Pallant, 2016). In this case, only one outlier is found between Perceived autonomy & Masculinity. As only one is found, no further action to remove this outlier will be taken.

Interpreting the results

The results are interpreted from the outputs in Appendix S-U. Appendix S contains all ANOVA outputs, Appendix T presents all Model Summary tables, and Appendix U contains all Coefficients outputs, where the predictor is specified within each output.

	ANOVA	
Predictor	**F**	**Sig.**
Power Distance	4.826	.030
Individualism	21.257	.000
Masculinity	20.973	.000
Uncertainty Avoidance	2.576	.112
Long Term Orientation	26.724	.000
Indulgence	1.365	.245

Table 3: ANOVA (Dependent variable: Perceived Autonomy)

The first thing to look at is the ANOVA table. This gives an indication if the model that is being measured is statistically significant, and if the predictor is making a statistically significant contribution to the dependent variable. This is determined by looking at the Sig. value of the model, where results below .05 suggests that the contribution is statistically significant. Table 3 above is a summary of the values of interest from each of the independent predictors.

It is found from the regression analyses that the predictors “Power Distance”, “Individualism”, “Masculinity”, and “Long Term Orientation” have values below .05, and thus, are making a statistically significant contribution to “Perceived Autonomy”.

The remaining predictors “Uncertainty Avoidance” and “Indulgence” have values above .05, which is suggesting that both those models are not statistically significant. This indicates that the data cannot provide evidence of an effect/prediction from the predictor on the dependent variable.

	Model Summary	
Predictor	**R Square**	**Adjusted R Square**
Power Distance	.045	.036
Individualism	.172	.164
Masculinity	.171	.162
Uncertainty Avoidance	.025	.015
Long Term Orientation	.208	.200
Indulgence	.013	.004

Table 4: Model Summary (Dependent variable: Perceived Autonomy)

The next point of interest in a regression analysis is the Model Summary, specifically the R Square values. These values explain how much of the variance in the dependent variable is explained by the predictor (Pallant, 2016). The regression analysis calculates two R Square values: R Square and Adjusted R Square. While the values both explain the same, the R Square tends to be rather optimistic in small sample sizes, and overestimates the variance explained. The Adjusted R Square corrects this overestimation (Pallant, 2016).

In table 4 above, the R Square and Adjusted R Square values are summarized and reported for each individual predictor. Since the sample size is a bit small (N=104), Adjusted R Square will be reported. It is found that “Individualism”, “Masculinity” and “Long Term Orientation” have the highest values, respectively at .172, .171, and .208. This means that in each simple linear regression model, 17.2 percent of the variance in “Perceived Autonomy” is explained by “Individualism”, 17.1 percent of the variance is explained by “Masculinity”, and 20.8 percent is explained by “Long Term Orientation”. The predictors “Power Distance”, “Uncertainty Avoidance”, and “Indulgence” have lower values, where 4.5 percent of the variance in “Perceived Autonomy” is explained by “Power Distance”, 2.5 percent is explained by “Uncertainty Avoidance”, and only 1.3 percent is explained by “Indulgence”.

	Coefficients	
Model	**Unstandardized Coefficients**	
	B	**Sig.**
(Constant)	3.851	
Power Distance	.345	.030
(Constant)	2.330	
Individualism	.692	.000
(Constant)	2.610	
Masculinity	.624	.000
(Constant)	4.229	
Uncertainty Avoidance	.251	.112
(Constant)	2.302	
Long Term Orientation	.747	.000
(Constant)	4.438	
Indulgence	.191	.245

Table 5: Coefficient (Dependent variable: Perceived Autonomy)

The final point of interest in the regression analysis is to see how (and if) the variable (predictor) included in the model predicts the dependent variable. In table 5 above, the Coefficients outputs are summarized for each simple linear regression analysis. The B value for each predictor under Unstandardized Coefficients (in table 5) explains the slope of the predictor, meaning that if the predictor increases by 1, the dependent variable will increase (or decrease if negative) with B. The Sig. values in table 5 are similar to the Sig. values in table 3 (ANOVA).

From table 5, it is found that “Individualism”, “Masculinity” and “Long Term Orientation” have the largest B values, indicating that these make the strongest contribution to explaining “Perceived Autonomy”. “Power Distance”, “Uncertainty Avoidance” and “Indulgence” make weaker contributions to explaining “Perceived Autonomy”.

From the simple linear regression analyses, the predictors’ contribution to explaining “Perceived Autonomy” ranked from strongest to weakest are:

1. Long Term Orientation
2. Individualism

3. Masculinity
4. Power Distance
5. Uncertainty Avoidance
6. Indulgence

5.3.3 Regression of Privacy Concerns

Although not a part of the hypotheses, it could be interesting to run the similar tests to Privacy Concerns, as was done to Perceived Autonomy in the previous section. Like before, checking assumptions to determine model fit is the first step.

Checking assumptions:

The Normal P-P Plot of Regression Standardized Residual and Scatterplot (both found in Appendix V) are investigated to check the assumptions, specified in 4.5.4.

All Normal P-P Plots show that the values reasonably follow the straight diagonal line from bottom left to top right, suggesting no major deviations from normality.

Each Scatterplot shows that the values have a reasonably rectangular distribution, in addition to being mostly grouped in the center around 0. This suggests that the data in the model shows homoscedasticity.

Lastly, outliers should also be identified. This is done by scanning the Scatterplots for values below -3.3 and above 3.3. Here, only one outlier is identified in the Scatterplot for Privacy Concerns & Masculinity, however, as only one is found, no further action to remove this outlier will be taken.

Interpreting the results:

Like before, the first step is to check if the models are significant. This is done by looking at ANOVA, specifically the Sig. value.

	ANOVA	
Predictor	**F**	**Sig.**
Power Distance	.000	.998
Individualism	.111	.740
Masculinity	.676	.413
Uncertainty Avoidance	3.140	.079
Long Term Orientation	.014	.905
Indulgence	.343	.559

Table 6: ANOVA (Dependent variable: Privacy Concerns)

Table 6, shown above, summarizes each ANOVA output from the analyses in Appendix W. From the table it is found that none of the predictors are making a statistically significant contribution to explaining Privacy Concerns (DV). This suggests that none of the predictors are good predictors of the outcome variable "Privacy Concerns".

Additionally from the Model Summary in Appendix X, it is found that all predictors explain very little of the variance in the dependent variable. All predictors have a negative Adjusted R Square, with the exception of "Uncertainty Avoidance", where the Adjusted R Square was at the low value of .020 (summarized in table 7 below).

	Model Summary	
Predictor	**R Square**	**Adjusted R Square**
Power Distance	.000	-.010
Individualism	.001	-.009
Masculinity	.007	-.003
Uncertainty Avoidance	.030	.020
Long Term Orientation	.000	-.010
Indulgence	.003	-.006

Table 7: Model Summary (Dependent variable: Privacy Concerns)

Even though the model fit was good, none of the predictors makes a statistically significant contribution to privacy concerns. This suggests that the cultural dimensions are poor predictors of privacy concerns. This assumption is also strengthened by the low Adjusted R Square values in Model Summary.

5.3.4 Summary of hypotheses

The hypotheses were the following:

H_1: A higher level of power distance contributes to lower consumer autonomy

H_2: A higher level of individualism contributes to higher consumer autonomy

H_3: A higher level of masculinity contributes to lower consumer autonomy

H_4: A higher level of uncertainty avoidance contributes to higher consumer autonomy

Hypothesis 1:

It was found from the simple regression analysis that masculinity makes a statistically significant contribution to explaining perceived autonomy. This contribution was interpreted by the B-value, which was .345. This indicates that when the "Power Distance" predictor increases by 1, the "Perceived Autonomy" will increase by .345. In total, both considering B value and the Sig. value, this means that power distance is making a statistically significant positive contribution to perceived autonomy.

Hypothesis 2:

The simple regression analysis showed that individualism makes a statistically significant contribution to explaining perceived autonomy. The contribution was measured by the B-value at .692. This suggests that individualism makes a statistically significant positive contribution to explaining perceived autonomy.

Hypothesis 3:

The regression analysis showed that masculinity makes a statistically significant contribution to perceived autonomy. The B-value, or how strong the contribution, was valued at .624, indicating that masculinity makes a positive contribution to predict perceived autonomy.

Hypothesis 4:

Running a regression analysis shows that uncertainty avoidance does not make a statistically significant contribution to perceived autonomy, as the Sig. value was well above .05 (specifically at .112). The B-value was .251, meaning that when “Uncertainty Avoidance” increases by 1, “Perceived Autonomy” increases by .251. This suggests a positive contribution to explaining perceived autonomy, however the results are statistically non-significant.

H_1: A higher level of power distance contributes to lower consumer autonomy	Not supported*
H_2: A higher level of individualism contributes to higher consumer autonomy	Supported*
H_3: A higher level of masculinity contributes to lower consumer autonomy	Not supported*
H_4: A higher level of uncertainty avoidance contributes to lower consumer autonomy	Not supported**

Table 8: Summary of hypotheses (* = statistically significant, ** = statistically non-significant)

6. Discussion

This section discusses the results and the existing literature, and presents it in a structural manner.

6.1 Power distance and its effect on perceived consumer autonomy

Based on the literature review it was hypothesized that a higher level of power distance would contribute to a lower consumer autonomy. Interestingly, the regression analysis finds that power distance makes a (statistically significant) positive contribution to predict perceived consumer autonomy. This means that the opposite contribution is found: a higher level of power distance contributes to a higher level of perceived consumer autonomy, and hence, not supporting the initial hypothesis.

Basabe (2005), Lee & Antonakis (2012), Conway et al. (1992) and Hofstede et al. (2011) all find that autonomy and power distance negatively correlate with each other, which implies that the results of this thesis finds a contradiction to the existing literature and research on the area. A possible explanation for this can lie within the nature of the construct. As mentioned in the abstract, the research and literature on relationships between *consumer autonomy* and Hofstede's cultural dimensions represent a large research gap, thus forcing a different approach. Basabe (2005), Lee & Antonakis (2012), Conway et al. (1992) and Hofstede et al. (2011) do not specifically assess the relationship between the dimensions and *consumer* autonomy, but rather autonomy on a general basis, and hence, may explain the difference between the results and the literature. Further research is needed to find the relationship between autonomy in decision-making and consumer situations.

Thus, the findings imply that higher levels of power distance contribute to consumer autonomy specifically.

6.2 Individualism and its effect on perceived consumer autonomy

Before the data was analyzed it was hypothesized on the basis of existing literature that a higher level of individualism contributes to higher consumer autonomy. The results of the analyses show that individualism provides a significant, positive contribution to explain consumer autonomy, thus supporting the initial hypothesis.

This result supports and confirms the findings of Triandis & Gelfand (2012), who suggest that it is common that individualistic people tend to be more autonomous. Similarly to the previous section(6.1), very little literature and research are found regarding specifically consumer autonomy. The result of this thesis provides new insights and adds to the existing literature by providing research on consumer autonomy, and suggests that autonomous decision-making and consumer autonomy both are predicted by the higher levels of individualism.

6.3 Masculinity and its effect on perceived consumer autonomy

It was hypothesized before the data was analyzed that a higher level of masculinity contributes to lower consumer autonomy. However, the result of the regression analysis in this thesis suggests that masculinity makes a statistically significant *positive* contribution to explaining consumer autonomy, thus implying that the opposite effect is true: a higher level of masculinity contributes to higher consumer autonomy.

The hypothesis was deduced from the literature, where Wang et al. (2017) and Richins & Dawson (1992) find that masculine cultures tend often to search for personal well-being in life, and followingly, Ditmar et al. (2014), Nagpaul & Pang (2016) and Wang et al. (2017) show that autonomy reduce well-being due to a low satisfaction by the psychological need for autonomy.

A possible explanation to the different results can again be that the literature do not specify predictions to *consumer* autonomy in specific. Regardless, as the research from the literature provides the opposite contribution compared to the result of the analysis, this thesis contributes with new insights and knowledge to the area of understanding the relationship between masculinity and consumer autonomy.

6.4 Uncertainty avoidance and its effect on perceived consumer autonomy

Finding no existing, consistent literature to support the specific relationship between uncertainty avoidance and consumer autonomy, a logical approach based on the tendencies of individuals with higher levels of uncertainty avoidance was used to form a hypothesis. It was hypothesized that a higher level of uncertainty avoidance contributes to lower consumer autonomy. The regression analysis shows that uncertainty avoidance does in fact make a positive contribution, but however, the contribution is statistically non-significant. This means that the result suggests a positive contribution of uncertainty avoidance on consumer autonomy, and not a negative, thus not initially supporting the hypothesized contribution.

However, the non-significant nature of the analysis may simply imply that the sample size was too small or that the random variation is too large to significantly predict the outcome (Pallant, 2016), suggesting that the opposite contribution may also be true. The insignificant nature of the relationship may indicate that not enough evidence is provided to successfully and accurately predict consumer autonomy.

6.5 Additional contributions on perceived consumer autonomy

No literature was found regarding the relationship between autonomy (both including consumer autonomy and autonomy on a general basis) and long term orientation and indulgence. Therefore, no hypotheses were created, but however, the regression analyses were still completed for the two remaining dimensions. The results of the analyses find that long term orientation makes a significant positive contribution to explaining consumer autonomy, while indulgence does not make a significant contribution.

The results and findings of this thesis therefore provides a unique contribution to the research of how a higher level of long term orientation and indulgence contributes to explain consumer autonomy, but further research should be employed to more closely analyze the relationship between these two dimensions and consumer autonomy.

7 Conclusions

In the developing age of artificial intelligence in marketing, studying consumer autonomy may be more important than ever. In societies with cultural diversity, ref. culture dimensions, there is no guarantee that all citizens (or nations) will react similarly to external influence on their consumer autonomy.

Hofstede's cultural dimensions, used to measure cultural attributes, are proposed in this thesis to predict and explain consumer autonomy. To study consumer autonomy in an age where artificial intelligence is becoming more and more widespread is highly relevant, as AI-recommendation technologies influences consumer choices and even manages to change consumers´ preferences (Franklin et al., 2022: Cha et al., 2019: Melumad et al., 2020: Murray & Haubl, 2009). The literature finds evidence that some of the cultural dimensions influence autonomy, but there is however very limited research on how the cultural dimensions influence the level of *consumer* autonomy, which makes this thesis a new and unique contribution to the field.

The study consists of one research question: Do cultural factors influence the level of consumer autonomy? In order to provide a detailed answer, the research question was extended to four hypotheses.

The thesis finds evidence that a higher level of power distance, individualism and masculinity all make significant positive contributions to consumer autonomy. Although not a part of the extended hypothesis, the study finds additionally that a higher level of long term orientation makes a significant positive contribution to explaining consumer autonomy.

In total, the thesis finds that cultural factors *do* influence the level of consumer autonomy, however, not all contributions are significant.

References

Ahmad, S., Wasim, S., Irfan, S., Gogoi, S., Srivastava, A., & Farheen, Z. (2019). Qualitative v/s. Quantitative Research- A Summarized Review. *Journal of Evidence Based Medicine and Healthcare*, *6*(43), 2828–2832. https://doi.org/10.18410/jebmh/2019/587

André, Q., Carmon, Z., Wertenbroch, K., Crum, A., Frank, D., Goldstein, W., Huber, J., van Boven, L., Weber, B., & Yang, H. (2017). Consumer Choice and Autonomy in the Age of Artificial Intelligence and Big Data. *Customer Needs and Solutions*, *5*(1-2), 28–37. https://doi.org/10.1007/s40547-017-0085-8

Arkkelin, D. (2014). Using SPSS to Understand Research and Data Analysis. *Psychology Curricular Materials*. https://scholar.valpo.edu/psych_oer/1

Basabe, N. (2005). Cultural dimensions and social behavior correlates: Individualism-Collectivism and Power Distance. *International Review of Social Psychology*. https://www.academia.edu/12857539/Cultural_dimensions_and_social_behavior_correlates_Individualism_Collectivism_and_Power_Distance?auto=citations&from=cover_page

Baumeister, R. F., & Monroe, A. E. (2014). Recent Research on Free Will. *Advances in Experimental Social Psychology*, 1–52. https://doi.org/10.1016/b978-0-12-800284-1.00001-1

Boyadzhieva, E. (2016). Learner-centered Teaching and Learner Autonomy. *Procedia - Social and Behavioral Sciences*, *232*, 35–40. https://doi.org/10.1016/j.sbspro.2016.10.008

Brooks, A. (2018, August 7). *50 Marketing AI & Machine Learning Statistics*. Venture Harbour. https://www.ventureharbour.com/marketing-ai-machine-learning-statistics/

Burns, E., & Kate Brush. (2021). *What is deep learning and how does it work?* Techtarget. https://www.techtarget.com/searchenterpriseai/definition/deep-learning-deep-neural-network

Capece, G., Calabrese, A., Di Pillo, F., Costa, R., & Crisciotti, V. (2013). The Impact of National Culture on E-commerce Acceptance: the Italian Case. *Knowledge and Process Management*, *20*(2), 102–112. https://doi.org/10.1002/kpm.1413

Carmon, Z., Schrift, R., Wertenbroch, K., & Yang, H. (2019). Designing AI Systems That Customers Won't Hate. *MITSloan*. https://www.researchgate.net/publication/338005754_Designing_AI_Systems_That_Customers_Won't_Hate/citations

Cha, N., Cho, H., Lee, S., & Hwang, J. (2019). Effect of AI Recommendation System on the Consumer Preference Structure in e-Commerce: Based on Two types of Preference. *2019 21st International Conference on Advanced Communication Technology (ICACT)*. https://doi.org/10.23919/icact.2019.8701967

Chen, B., Vansteenkiste, M., Beyers, W., Boone, L., Deci, E. L., Van der Kaap-Deeder, J., Duriez, B., Lens, W., Matos, L., Mouratidis, A., Ryan, R. M., Sheldon, K. M., Soenens, B., Van Petegem, S., & Verstuyf, J. (2014). Basic psychological need satisfaction, need frustration, and need strength across four cultures. *Motivation and Emotion*, *39*(2), 216–236. https://doi.org/10.1007/s11031-014-9450-1

Chen, B., Vansteenkiste, M., Beyers, W., Soenens, B., & Van Petegem, S. (2013). Autonomy in Family Decision Making for Chinese Adolescents. *Journal of Cross-Cultural Psychology*, *44*(7), 1184–1209. https://doi.org/10.1177/0022022113480038

Chien, C.-F., Dauzère-Pérès, S., Huh, W. T., Jang, Y. J., & Morrison, J. R. (2020). Artificial intelligence in manufacturing and logistics systems: algorithms, applications, and case studies. *International Journal of Production Research*, *58*(9), 2730–2731. https://doi.org/10.1080/00207543.2020.1752488

Clark, C. J., Luguri, J. B., Ditto, P. H., Knobe, J., Shariff, A. F., & Baumeister, R. F. (2014). Free to punish: A motivated account of free will belief. *Journal of Personality and Social Psychology*, *106*(4), 501–513. https://doi.org/10.1037/a0035880

Clark, L. A., & Watson, D. (1995). Constructing validity: Basic issues in objective scale development. *Psychological Assessment*, *7*(3), 309–319. https://doi.org/10.1037/1040-3590.7.3.309

Conway, T. L., Vickers, R. R., & French, J. R. P. (1992). An Application of Person-Environment Fit Theory: Perceived Versus Desired Control. *Journal of Social Issues*, *48*(2), 95–107. https://doi.org/10.1111/j.1540-4560.1992.tb00886.x

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2019). How Artificial Intelligence Will Change the Future of Marketing. *Journal of the Academy of Marketing Science*, *48*(1), 24–42. Springer. https://doi.org/10.1007/s11747-019-00696-0

de Mooij, M., & Hofstede, G. (2002). Convergence and divergence in consumer behavior: implications for international retailing. *Journal of Retailing*, *78*(1), 61–69. https://doi.org/10.1016/s0022-4359(01)00067-7

Deci, E. L., & Ryan, R. M. (2008). Self-determination theory: A macrotheory of human motivation, development, and health. *Canadian Psychology*, *49*(3), 182–185. https://doi.org/10.1037/a0012801

Deci, E. L., & Ryan, R. M. (2014). Autonomy and Need Satisfaction in Close Relationships: Relationships Motivation Theory. *Human Motivation and Interpersonal Relationships*, 53–73. https://doi.org/10.1007/978-94-017-8542-6_3

Devassy, B., & George, S. (2021). Estimation of strawberry firmness using hyperspectral imaging: a comparison of regression models. *Journal of Spectral Imaging*. https://doi.org/10.1255/jsi.2021.a3

DeVellis, R. F. (2012). *Scale development: theory and applications* (3rd ed.). Thousand Oaks, California: SAGE.

Dhar, R., & Wertenbroch, K. (2012). Self-Signaling and the Costs and Benefits of Temptation in Consumer Choice. *Journal of Marketing Research*, *49*(1), 15–25. https://doi.org/10.1509/jmr.10.0490

Dittmar, H., Bond, R., Hurst, M., & Kasser, T. (2014). The relationship between materialism and personal well-being: A meta-analysis. *Journal of Personality and Social Psychology*, *107*(5), 879–924. https://doi.org/10.1037/a0037409

Drumwright, M. (2018). Ethical issues in marketing, advertising, and sales. In *The Routledge Companion to Business Ethics* (pp. 506-522). Routledge.

Eggers, F., Sattler, H., Teichert, T., & Völckner, F. (2022). Choice-Based Conjoint Analysis. *Handbook of Market Research*, 781–819. https://doi.org/10.1007/978-3-319-57413-4_23

EU. (2022). *Data protection in the EU*. European Commission. https://ec.europa.eu/info/law/law-topic/data-protection/data-protection-eu_en#documents

Eylon, D., & Au, K. Y. (1999). Exploring empowerment cross-cultural differences along the power distance dimension. *International Journal of Intercultural Relations*, *23*(3), 373–385. https://doi.org/10.1016/s0147-1767(99)00002-4

Fang, H., Zhang, J., Bao, Y., & Zhu, Q. (2013). Towards effective online review systems in the Chinese context: A cross-cultural empirical study. *Electronic Commerce Research and Applications*, *12*(3), 208–220. https://doi.org/10.1016/j.elerap.2013.03.001

Feather, N. T., & Simon, J. G. (1971). Causal attributions for success and failure in relation to expectations of success based upon selective or manipulative control. *Journal of Personality*, *39*(4), 527–541. https://doi.org/10.1111/j.1467-6494.1971.tb00060.x

Franklin, M., Ashton, H., Gorman, R., & Armstrong, S. (2022). Recognising the importance of preference change: A call for a coordinated multidisciplinary research effort in the age of AI. In *arXiv*. https://arxiv.org/pdf/2203.10525.pdf

Gentsch, P. (2019). *AI in marketing, sales and service: how marketers without a data science degree can use AI, big data and bots* (1st ed.). Palgrave Macmillan.

Ger, G., & Belk, R. W. (1996). Cross-cultural differences in materialism. *Journal of Economic Psychology*, *17*(1), 55–77. https://doi.org/10.1016/0167-4870(95)00035-6

Glazer, S. (2021). Organizational role ambiguity as a proxy for uncertainty avoidance. *International Journal of Intercultural Relations*, *85*, 1–12. https://doi.org/10.1016/j.ijintrel.2021.08.011

Goertzen, M. J. (2017). Chapter 3. Introduction to Quantitative Research and Data. *Library Technology Reports*, *53*(4), 12–18. https://journals.ala.org/index.php/ltr/article/view/6325/8274

Haugstulen, E. K. (2021). “You might also like” -The technological consumers understanding of transparent AI. *NTNU Open*. https://hdl.handle.net/11250/2780460

Heath, E., Kaldis, B., & Marcoux, A. M. (2018). *The Routledge companion to business ethics*. Routledge.

Helskyaho, H., Yu, J., & Yu, K. (2021). Introduction to Machine Learning. *Machine Learning for Oracle Database Professionals*, 1–22. https://doi.org/10.1007/978-1-4842-7032-5_1

Hofstede, G. (2011). Dimensionalizing Cultures: The Hofstede Model in Context. *Online Readings in Psychology and Culture*, *2*(1), 1–26. https://doi.org/10.9707/2307-0919.1014

Hofstede, G., & Minkov, M. (2013). *V S M 2013 VALUES SURVEY MODULE 2013 MANUAL Contents Page*. https://geerthofstede.com/wp-content/uploads/2016/07/Manual-VSM-2013.pdf

Huang, M.-H., & Rust, R. T. (2020). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science*, *49*(1). https://doi.org/10.1007/s11747-020-00749-9

IBM Security. (2021). *Cost of a Data Breach Report 2021*. https://www.ibm.com/downloads/cas/OJDVQGRY

Jones, L. S., & Hiller, J. S. (2021, March 22). *Who's Keeping Score: Oversight of Changing Consumer Credit Infrastructure*. SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3805751

Kahneman, D. (2011). *Thinking, Fast and Slow*. Farrar, Straus And Giroux.

Kane, R. (2011). *The Oxford handbook of free will* (2nd ed.). Oxford University Press.

Kannan, P. K., & Li, H. A. (2017). *Digital marketing: A framework, review and research agenda*. International Journal of Research in Marketing. https://doi.org/10.1016/j.ijresmar.2016.11.006

Kerry, C. F. (2020, February 10). *Protecting privacy in an AI-driven world*. Brookings. https://www.brookings.edu/research/protecting-privacy-in-an-ai-driven-world/
Kumari, K., & Yadav, S. (2018). Linear regression analysis study. *Journal of the Practice of Cardiovascular Sciences*, *4*(1), 33–36. https://doi.org/10.4103/jpcs.jpcs_8_18
LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep Learning. *Nature*, *521*(7553), 436–444. https://doi.org/10.1038/nature14539
Lee, Y., & Antonakis, J. (2012). When Preference Is Not Satisfied but the Individual Is. *Journal of Management*, *40*(3), 641–675. https://doi.org/10.1177/0149206311436080
Lunt, M. (2013). Introduction to statistical modeling: linear regression: Fig. 1. *Rheumatology*, *54*(7), 1137–1140. https://doi.org/10.1093/rheumatology/ket146
Mahesh, B. (2019). *Machine Learning Algorithms - A Review*. Researchgate. https://www.researchgate.net/publication/344717762_Machine_Learning_Algorithms_-A_Review
Markus, H. R., & Kitayama, S. (2010). Cultures and selves: A cycle of mutual constitution. *Perspectives on Psychological Science*, *5*(4), 420–430. https://doi.org/10.1177/1745691610375557
Markus, H. R., & Schwartz, B. (2010). Does Choice Mean Freedom and Well-Being? *Journal of Consumer Research*, *37*(2), 344–355. https://doi.org/10.1086/651242
Mazurek, G., & Małagocka, K. (2019). Perception of privacy and data protection in the context of the development of artificial intelligence. *Journal of Management Analytics*, *6*(4), 344–364. https://doi.org/10.1080/23270012.2019.1671243
Melumad, S., Hadi, R., Hildebrand, C., & Ward, A. F. (2020). Technology-Augmented Choice: How Digital Innovations Are Transforming Consumer Decision Processes. *Customer Needs and Solutions*. https://doi.org/10.1007/s40547-020-00107-4
Michaelsen, P., Johansson, L.-O., & Hedesström, M. (2021). Experiencing default nudges: autonomy, manipulation, and choice-satisfaction as judged by people themselves. *Behavioral Public Policy*, 1–22. https://doi.org/10.1017/bpp.2021.5
Mishra, R., Kr Singh, R., & Koles, B. (2020). Consumer decision‐making in Omnichannel retailing: Literature review and future research agenda. *International Journal of Consumer Studies*. https://doi.org/10.1111/ijcs.12617
Möller, J., & Eisend, M. (2010). A Global Investigation into the Cultural and Individual Antecedents of Banner Advertising Effectiveness. *Journal of International Marketing*, *18*(2), 80–98. https://doi.org/10.1509/jimk.18.2.80
Murray, K. B., & Häubl, G. (2009). Personalization without Interrogation: Towards more Effective Interactions between Consumers and Feature-Based Recommendation Agents. *Journal of Interactive Marketing*, *23*(2), 138–146. https://doi.org/10.1016/j.intmar.2009.02.009
Murray, K. B., & Schlacter, J. L. (1990). The impact of services versus goods on consumers' assessment of perceived risk and variability. *Journal of the Academy of Marketing Science*, *18*(1), 51–65. https://doi.org/10.1007/bf02729762
Nair, K., & Gupta, R. (2021). Application of AI technology in modern digital marketing environment. *World Journal of Entrepreneurship, Management and Sustainable Development*. https://doi.org/10.1108/wjemsd-08-2020-0099
Niemiec, C. P., & Ryan, R. M. (2009). Autonomy, competence, and relatedness in the classroom. *Theory and Research in Education*, *7*(2), 133–144. https://doi.org/10.1177/1477878509104318
Ogden, H., & Cheng, S. (2011). Cultural dimensions and materialism: comparing Canada and China. *Asia Pacific Journal of Marketing and Logistics*, *23*(4), 431–447. https://doi.org/10.1108/13555851111165011

Omoregie, J. (2015). *Freewill : the degree of freedom within*. Authorhouse.
Padden, M., & Öjehag-Pettersson, A. (2021). Protected how? Problem representations of risk in the General Data Protection Regulation (GDPR). *Critical Policy Studies*, *15*(4), 486–503. https://doi.org/10.1080/19460171.2021.1927776
Pallant, J. (2016). *SPSS survival manual: A step by step guide to data analysis using IBM SPSS* (6th ed.). Mcgraw-Hill.
Panesar, A. (2020). Machine Learning Algorithms. *Machine Learning and AI for Healthcare*, 85–144. https://doi.org/10.1007/978-1-4842-6537-6_4
Pradeep, A. K., Appel, A., & Sthanunathan, S. (2019). *AI for marketing and product innovation : powerful new tools for predicting trends, connecting with customers, and closing sales*. John Wiley & Sons.
Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2020). Consumers and Artificial Intelligence: An Experiential Perspective. *Journal of Marketing*, *85*(1), 002224292095384. https://doi.org/10.1177/0022242920953847
Rainie, L. (2019). *Facebook Algorithms and Personal Data*. Pew Research Center. https://www.academia.edu/39128831/Facebook_Algorithms_and_Personal_Data?from=cover_page
Richins, M. L., & Dawson, S. (1992). A Consumer Values Orientation for Materialism and Its Measurement: Scale Development and Validation. *Journal of Consumer Research*, *19*(3), 303–316. https://doi.org/10.1086/209304
Russell, P. (2021). *Artificial intelligence : a modern approach, global edition.* Pearson Education Limited.
Rust, R. T. (2019). The future of marketing. *International Journal of Research in Marketing*, *37*(1). https://doi.org/10.1016/j.ijresmar.2019.08.002
Sawtooth. (2022). *Adaptive Conjoint Analysis*. Sawtoothsoftware. https://sawtoothsoftware.com/conjoint-analysis/aca
Skinner, E. A. (1996). A guide to constructs of control. *Journal of Personality and Social Psychology*, *71*(3), 549–570. https://doi.org/10.1037/0022-3514.71.3.549
Stahl, B. C., & Wright, D. (2018). Ethics and Privacy in AI and Big Data: Implementing Responsible Research and Innovation. *IEEE Security & Privacy*, *16*(3), 26–33. https://doi.org/10.1109/msp.2018.2701164
Tellis, G. J., Stremersch, S., & Yin, E. (2003). The International Takeoff of New Products: The Role of Economics, Culture, and Country Innovativeness. *Marketing Science*, *22*(2), 188–208. https://doi.org/10.1287/mksc.22.2.188.16041
Triandis, H. C., & Gelfand, M. J. (2012). A Theory of Individualism and Collectivism. *Handbook of Theories of Social Psychology*, 498–520. https://doi.org/10.4135/9781446249222.n51
Vishnoi, S. K., Bagga, T., Sharma, A., & Wani, S. N. (2018). Artificial intelligence enabled marketing solutions: A review. *Indian Journal of Economics & Business*, *17*(4), 167–177.
Vlačić, B., Corbo, L., Costa e Silva, S., & Dabić, M. (2021). The evolving role of artificial intelligence in marketing: A review and research agenda. *Journal of Business Research*, *128*, 187–203. https://doi.org/10.1016/j.jbusres.2021.01.055
Voss, W. G., & Bouthinon-Dumas, H. (2021). EU GENERAL DATA PROTECTION REGULATION SANCTIONS IN THEORY AND IN PRACTICE. *Santa Clara High Technology Law Journal*, *37*(1), 1. https://digitalcommons.law.scu.edu/chtlj/vol37/iss1/2/

Wagner, J. A. (1995). Studies of Individualism-Collectivism: Effects on Cooperation in Groups. *Academy of Management Journal*, *38*(1), 152–173. https://doi.org/10.5465/256731

Wang, R., Liu, H., Jiang, J., & Song, Y. (2017). Will materialism lead to happiness? A longitudinal analysis of the mediating role of psychological needs satisfaction. *Personality and Individual Differences*, *105*, 312–317. https://doi.org/10.1016/j.paid.2016.10.014

Watson, R. (2015). Quantitative Research. *Nursing Standard*, *29*(31), 44–48. https://doi.org/10.7748/ns.29.31.44.e8681

Wegner, D. M. (2004). Précis of The illusion of conscious will. *Behavioral and Brain Sciences*. https://doi.org/10.1017/s0140525x04000159

Wegner, D. M., & Wheatley, T. (1999). Apparent mental causation: Sources of the experience of will. *American Psychologist*, *54*(7), 480–492. https://doi.org/10.1037/0003-066x.54.7.480

Wertenbroch, K., Schrift, R. Y., Alba, J. W., Barasch, A., Bhattacharjee, A., Giesler, M., Knobe, J., Lehmann, D. R., Matz, S., Nave, G., Parker, J. R., Puntoni, S., Zheng, Y., & Zwebner, Y. (2020). Autonomy in consumer choice. *Marketing Letters 31*, 429–439. https://doi.org/10.1007/s11002-020-09521-z

Whitney, L. (2021, August 17). *Data privacy is a growing concern for more consumers*. TechRepublic. https://www.techrepublic.com/article/data-privacy-is-a-growing-concern-for-more-consumers/

Wilson, M. (2016). When creative consumers go green: understanding consumer upcycling. *Journal of Product & Brand Management*, *25*(4), 394–399. https://doi.org/10.1108/jpbm-09-2015-0972

Wirtz, J., Lwin, M. O., & Williams, J. D. (2007). Causes and consequences of consumer online privacy concern. *International Journal of Service Industry Management*, *18*(4), 326–348. https://doi.org/10.1108/09564230710778128

Yin, S., & Kaynak, O. (2015). *Big Data for Modern Industry: Challenges and Trends [Point of View]*. Ieeexplore. https://doi.org/10.1109/jproc.2015.2388958

Appendix A - Frequencies (Demographics)

Statistics

		Gender	AgeGroup	Country
N	Valid	104	104	104
	Missing	0	0	0

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	56	53.8	53.8	53.8
	Female	45	43.3	43.3	97.1
	Will not specify	3	2.9	2.9	100.0
	Total	104	100.0	100.0	

AgeGroup

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Under 20	5	4.8	4.8	4.8
	20-24	22	21.2	21.2	26.0
	25-29	23	22.1	22.1	48.1
	30-34	10	9.6	9.6	57.7
	35-39	5	4.8	4.8	62.5
	40-49	17	16.3	16.3	78.8
	50-59	12	11.5	11.5	90.4
	60 or over	10	9.6	9.6	100.0
	Total	104	100.0	100.0	

Country

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Norway	104	100.0	100.0	100.0

Appendix B - Descriptives (Perceived Autonomy)

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error
I feel a sense of choice and freedom in the choice I made	104	1	7	5.56	1.378	-1.223	.237
I feel that my decision reflected what I really want	104	1	7	5.43	1.406	-.854	.237
I feel my choice expresses who I really am	104	1	7	4.89	1.365	-.226	.237
I feel I chose what really interests me	104	1	7	5.31	1.394	-.657	.237
Choosing made me feel like "I had to"	104	1	7	4.36	1.789	-.386	.237
I felt forced to make a choice which I normally wouldn't do	104	1	7	5.02	1.795	-.553	.237
I felt pressured to make the choice	104	1	7	5.26	1.806	-.770	.237
Making a choice felt like an obligation	104	1	7	4.68	1.845	-.353	.237
I felt in control of my choice	104	1	7	5.39	1.610	-.881	.237
I felt that my choices belonged to me	104	1	7	5.50	1.514	-.950	.237
My choice reflected my preferences	104	1	7	5.42	1.499	-.845	.237
The choice I made were free from external influence	104	1	7	4.79	1.810	-.800	.237
Valid N (listwise)	104						

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error
PerceivedAutonomy	104	2.67	7.00	5.1346	1.03936	-.185	.237
Valid N (listwise)	104						

Appendix C - Descriptives (Privacy Concerns)

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error
How concerned would you be that your personal data may be used for purposes other than the reason you provided the information for?	104	1	7	5.17	1.622	-.843	.237
How concerned would you be about your online personal privacy?	104	1	7	4.88	1.591	-.648	.237
How concerned would you be about the fact that sites you visited might be known/tracked?	104	1	7	4.99	1.445	-.672	.237
How concerned would you be about your personal information being shared with other parties?	104	1	7	5.20	1.516	-1.015	.237
How concerned are you about disclosing your financial information?	104	1	7	5.02	1.625	-.765	.237
Valid N (listwise)	104						

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error
PrivacyConcerns	104	1.00	7.00	5.0538	1.30369	-.907	.237
Valid N (listwise)	104						

Appendix D - Tests of normality

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
PerceivedAutonomy	.130	104	.000	.945	104	.000
PrivacyConcerns	.118	104	.001	.941	104	.000
PowerDistance	.126	104	.000	.968	104	.012
Individualism	.161	104	.000	.937	104	.000
Masculinity	.157	104	.000	.936	104	.000
UncertaintyAvoidance	.181	104	.000	.954	104	.001
LongTermOrientation	.136	104	.000	.961	104	.004
Indulgence	.173	104	.000	.947	104	.000
Gender	.349	104	.000	.698	104	.000
AgeGroup	.209	104	.000	.901	104	.000
Country	.	104	.	.	104	.

a. Lilliefors Significance Correction

Appendix E - Adaptive Conjoint Analysis

Descriptive Statistics

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
ACA Autonomy	104	38.8696970	2.24200937	41.1117063	20.3533866	9.20257018	84.687	.259	.237	-.558	.469
ACA Privacy	104	37.3111134	1.96637178	39.2774852	20.8568934	9.80464829	96.131	.101	.237	-1.004	.469
Price	104	31.8292190	7.44829878	39.2775178	23.3960154	7.02857459	49.401	.035	.237	-.660	.469
Discount	104	31.2014708	9.54653206	40.7480029	25.3120528	5.70835386	32.585	.297	.237	.370	.469
AI preference	104	26.7680364	.525304101	27.2933405	10.0816518	6.47402313	41.913	.659	.237	-.380	.469
Valid N (listwise)	104										

Appendix F - Reliability of Perceived autonomy

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.872	.878	12

Inter-Item Correlation Matrix

	I feel a sense of choice and freedom in the choice I made	I feel that my decision reflected what I really want	I feel my choice expresses who I really am	I feel I chose what really interests me	Choosing made me feel like "I had to"	I felt forced to make a choice which I normally wouldn't do	I felt pressured to make the choice	Making a choice felt like an obligation	I felt in control of my choice	I felt that my choices belonged to me	My choice reflected my preferences	The choice I made were free from external influence
I feel a sense of choice and freedom in the choice I made	1.000	.706	.563	.622	.017	.325	.269	.215	.421	.363	.458	.305
I feel that my decision reflected what I really want	.706	1.000	.621	.789	.050	.308	.322	.274	.379	.436	.576	.506
I feel my choice expresses who I really am	.563	.621	1.000	.650	-.068	.112	.125	.037	.306	.219	.407	.333
I feel I chose what really interests me	.622	.789	.650	1.000	.069	.343	.327	.227	.456	.423	.555	.446
Choosing made me feel like "I had to"	.017	.050	-.068	.069	1.000	.536	.443	.532	.025	.091	.182	-.048
I felt forced to make a choice which I normally wouldn't do	.325	.308	.112	.343	.536	1.000	.831	.705	.343	.447	.509	.237
I felt pressured to make the choice	.269	.322	.125	.327	.443	.831	1.000	.721	.318	.385	.479	.252
Making a choice felt like an obligation	.215	.274	.037	.227	.532	.705	.721	1.000	.229	.273	.414	.128
I felt in control of my choice	.421	.379	.306	.456	.025	.343	.318	.229	1.000	.679	.522	.319
I felt that my choices belonged to me	.363	.436	.219	.423	.091	.447	.385	.273	.679	1.000	.659	.489
My choice reflected my preferences	.458	.576	.407	.555	.182	.509	.479	.414	.522	.659	1.000	.502
The choice I made were free from external influence	.305	.506	.333	.446	-.048	.237	.252	.128	.319	.489	.502	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
I feel a sense of choice and freedom in the choice I made	56.06	135.492	.566	.578	.862
I feel that my decision reflected what I really want	56.18	131.937	.670	.753	.857
I feel my choice expresses who I really am	56.72	140.145	.419	.520	.870
I feel I chose what really interests me	56.31	132.390	.662	.699	.857
Choosing made me feel like "I had to"	57.26	140.893	.270	.392	.882
I felt forced to make a choice which I normally wouldn't do	56.60	124.709	.689	.774	.853
I felt pressured to make the choice	56.36	125.804	.654	.737	.856
Making a choice felt like an obligation	56.93	129.267	.546	.615	.864
I felt in control of my choice	56.22	132.970	.539	.534	.864
I felt that my choices belonged to me	56.12	131.676	.622	.645	.859
My choice reflected my preferences	56.19	128.176	.741	.611	.852
The choice I made were free from external influence	56.83	133.310	.454	.396	.870

Appendix G - Reliability of Privacy Concerns

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.891	.893	5

Inter-Item Correlation Matrix

	How concerned would you be that your personal data may be used for purposes other than the reason you provided the information for?	How concerned would you be about your online personal privacy?	How concerned would you be about the fact that sites you visited might be known/tracked?	How concerned would you be about your personal information being shared with other parties?	How concerned are you about disclosing your financial information?
How concerned would you be that your personal data may be used for purposes other than the reason you provided the information for?	1.000	.712	.589	.641	.507
How concerned would you be about your online personal privacy?	.712	1.000	.621	.714	.609
How concerned would you be about the fact that sites you visited might be known/tracked?	.589	.621	1.000	.723	.591
How concerned would you be about your personal information being shared with other parties?	.641	.714	.723	1.000	.538
How concerned are you about disclosing your financial information?	.507	.609	.591	.538	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
How concerned would you be that your personal data may be used for purposes other than the reason you provided the information for?	20.10	27.602	.719	.555	.872
How concerned would you be about your online personal privacy?	20.38	26.841	.796	.656	.854
How concerned would you be about the fact that sites you visited might be known/tracked?	20.28	28.844	.745	.592	.866
How concerned would you be about your personal information being shared with other parties?	20.07	27.772	.777	.647	.859
How concerned are you about disclosing your financial information?	20.25	28.597	.647	.446	.888

Appendix H - Reliability of Power Distance

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.165	.168	4

Inter-Item Correlation Matrix

	HofQ2	HofQ7	HofQ20	HofQ23
HofQ2	1.000	.172	-.114	.169
HofQ7	.172	1.000	.040	-.004
HofQ20	-.114	.040	1.000	.026
HofQ23	.169	-.004	.026	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
HofQ2	10.03	3.407	.139	.074	.056
HofQ7	10.51	3.068	.104	.034	.089
HofQ20	11.15	3.685	-.014	.019	.253
HofQ23	10.71	3.023	.095	.032	.102

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	.048	-.114	.172	.285	-1.511	.011	4

Appendix I - Reliability of Individualism

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.671	.672	4

Inter-Item Correlation Matrix

	HofQ1	HofQ4	HofQ6	HofQ9
HofQ1	1.000	.325	.385	.247
HofQ4	.325	1.000	.451	.284
HofQ6	.385	.451	1.000	.341
HofQ9	.247	.284	.341	1.000

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	.339	.247	.451	.204	1.825	.005	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
HofQ1	12.15	3.743	.424	.187	.628
HofQ4	12.00	3.981	.478	.245	.590
HofQ6	11.99	3.563	.541	.300	.543
HofQ9	12.52	4.271	.377	.148	.651

Appendix J - Reliability of Masculinity

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.729	.729	4

Inter-Item Correlation Matrix

	HofQ3	HofQ5	HofQ8	HofQ10
HofQ3	1.000	.481	.460	.322
HofQ5	.481	1.000	.387	.471
HofQ8	.460	.387	1.000	.293
HofQ10	.322	.471	.293	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
HofQ3	12.25	4.422	.547	.324	.651
HofQ5	11.90	4.476	.591	.360	.626
HofQ8	12.30	4.833	.485	.255	.687
HofQ10	12.07	4.821	.456	.242	.705

Appendix K - Reliability of Uncertainty Avoidance

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.360	.352	4

Inter-Item Correlation Matrix

	HofQ15	HofQ18	HofQ21	HofQ24
HofQ15	1.000	.176	.104	.010
HofQ18	.176	1.000	.256	-.054
HofQ21	.104	.256	1.000	.225
HofQ24	.010	-.054	.225	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
HofQ15	11.22	4.271	.146	.035	.342
HofQ18	10.53	3.572	.191	.101	.296
HofQ21	10.28	2.805	.338	.125	.092
HofQ24	10.84	3.808	.105	.064	.397

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	.120	-.054	.256	.309	-4.768	.014	4

Appendix L - Reliability of Long Term Orientation

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.553	.571	4

Inter-Item Correlation Matrix

	HofQ13	HofQ14	HofQ19	HofQ22
HofQ13	1.000	.430	.466	.241
HofQ14	.430	1.000	.042	.031
HofQ19	.466	.042	1.000	.289
HofQ22	.241	.031	.289	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
HofQ13	11.24	3.738	.587	.397	.286
HofQ14	11.86	4.474	.209	.219	.590
HofQ19	11.27	4.121	.366	.276	.457
HofQ22	11.15	4.306	.248	.100	.560

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	.250	.031	.466	.435	15.129	.031	4

Appendix M - Reliability of Indulgence

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.269	.275	4

Inter-Item Correlation Matrix

	HofQ11	HofQ12	HofQ16	HofQ17
HofQ11	1.000	.142	.265	-.248
HofQ12	.142	1.000	.072	.075
HofQ16	.265	.072	1.000	.214
HofQ17	-.248	.075	.214	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
HofQ11	9.93	3.170	.087	.187	.278
HofQ12	10.56	2.735	.159	.033	.184
HofQ16	9.94	2.754	.310	.153	.002
HofQ17	10.96	3.532	.014	.155	.354

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	.087	-.248	.265	.512	-1.069	.030	4

Appendix N - Reliability of Power Distance without item 3

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.253	.275	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
HofQ2	7.05	2.318	.241	.058	-.008[a]
HofQ7	7.53	2.252	.095	.031	.282
HofQ23	7.73	2.179	.095	.030	.287

a. The value is negative due to a negative average covariance among items. This violates reliability model assumptions. You may want to check item codings.

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	.112	-.004	.172	.176	-41.136	.008	3

Appendix O - Reliability of Power Distance without items 3 and 4

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.287	.293	2

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
HofQ2	3.63	1.130	.172	.029	.
HofQ7	4.11	.736	.172	.029	.

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	.172	.172	.172	.000	1.000	.000	2

Appendix P - Reliability of Uncertainty Avoidance without item 4

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.397	.395	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
HofQ15	7.77	2.801	.174	.035	.405
HofQ18	7.08	1.975	.297	.088	.176
HofQ21	6.83	1.834	.246	.069	.290

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	.179	.104	.256	.152	2.468	.005	3

Appendix Q - Reliability of Indulgence without item 4

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.354	.363	3

Item-Total Statistics

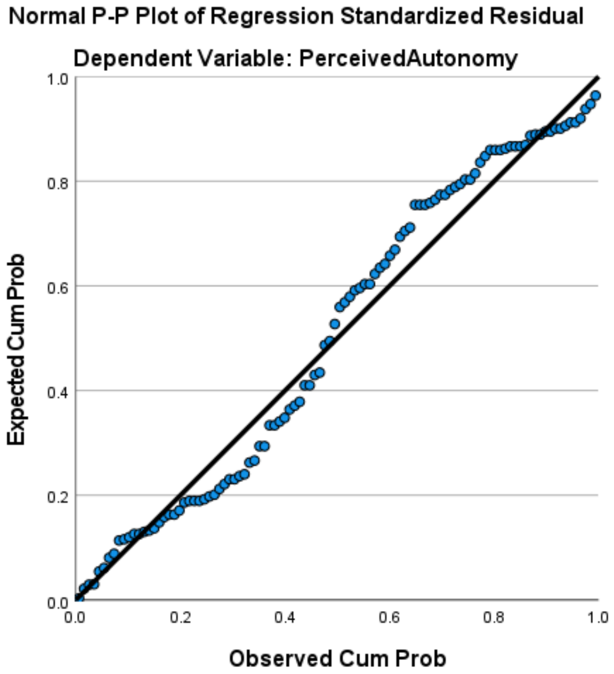
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
HofQ11	7.10	1.932	.268	.085	.133
HofQ12	7.72	2.048	.137	.021	.417
HofQ16	7.11	2.251	.217	.071	.248

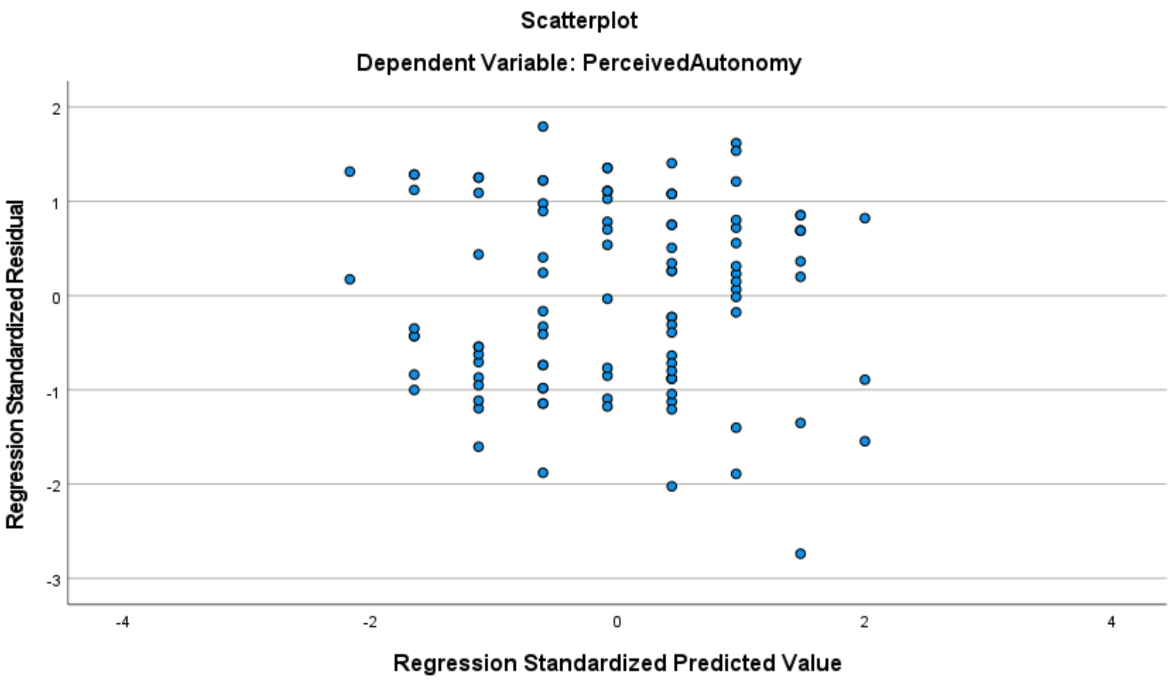
Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance	N of Items
Inter-Item Correlations	.160	.072	.265	.192	3.653	.008	3

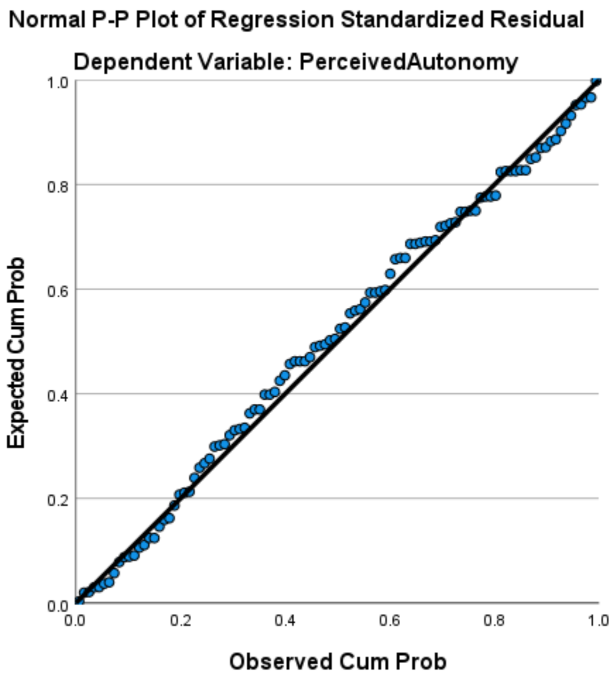
Appendix R - Checking assumptions (DV: Perceived Autonomy)

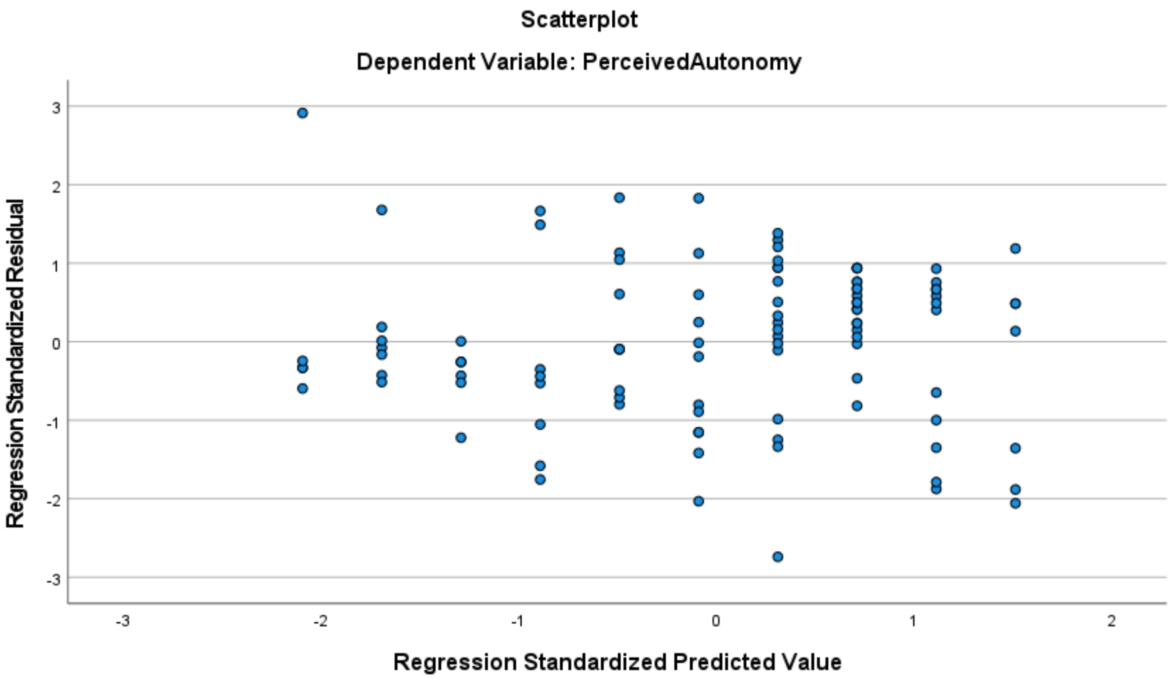
Perceived autonomy & Power Distance:



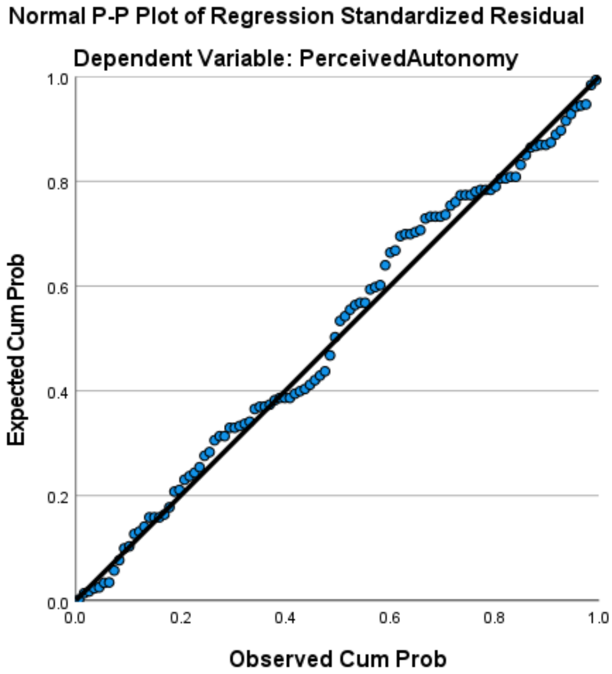


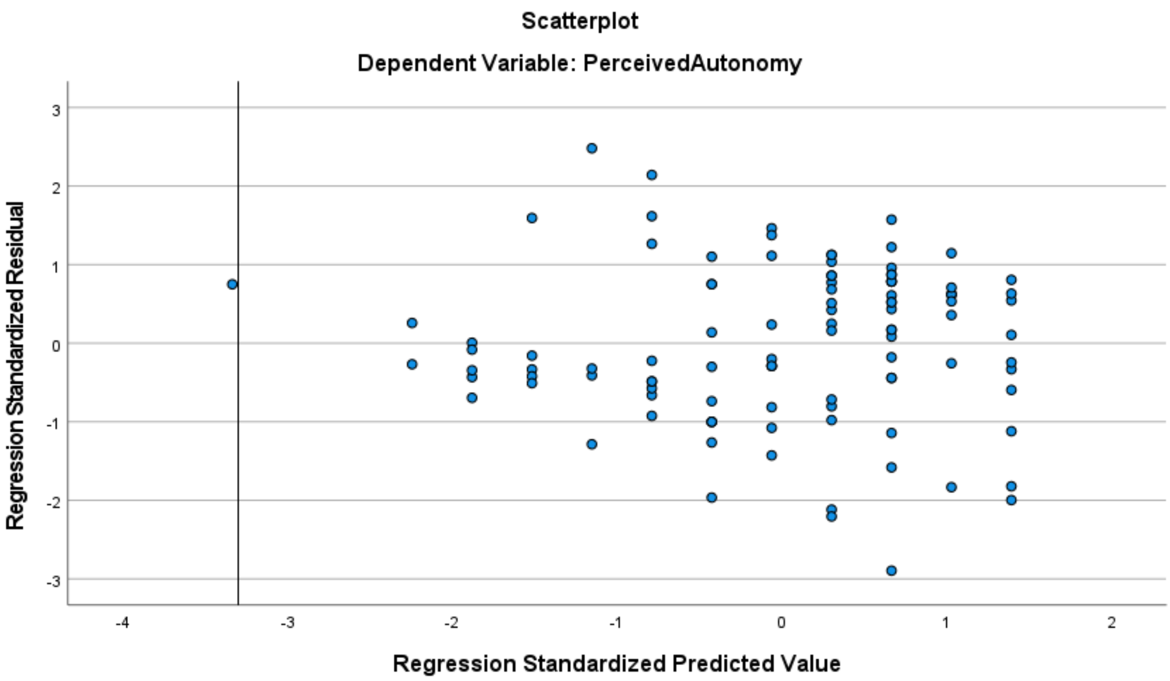
Perceived autonomy & Individualism:



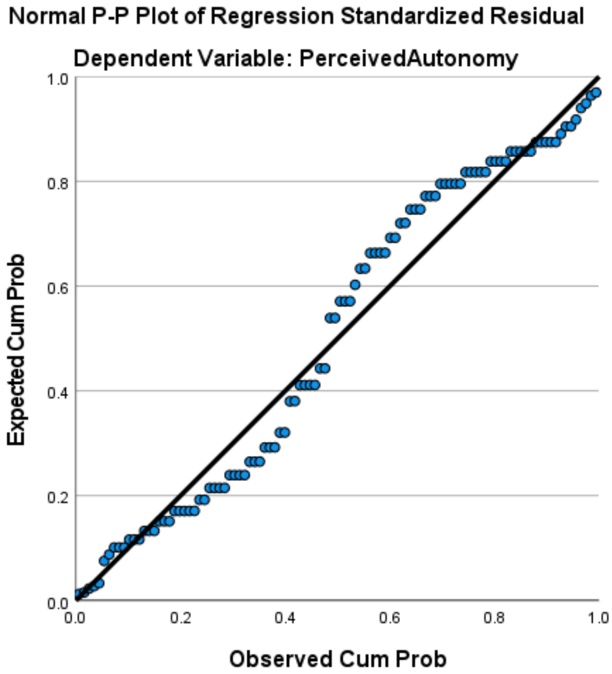


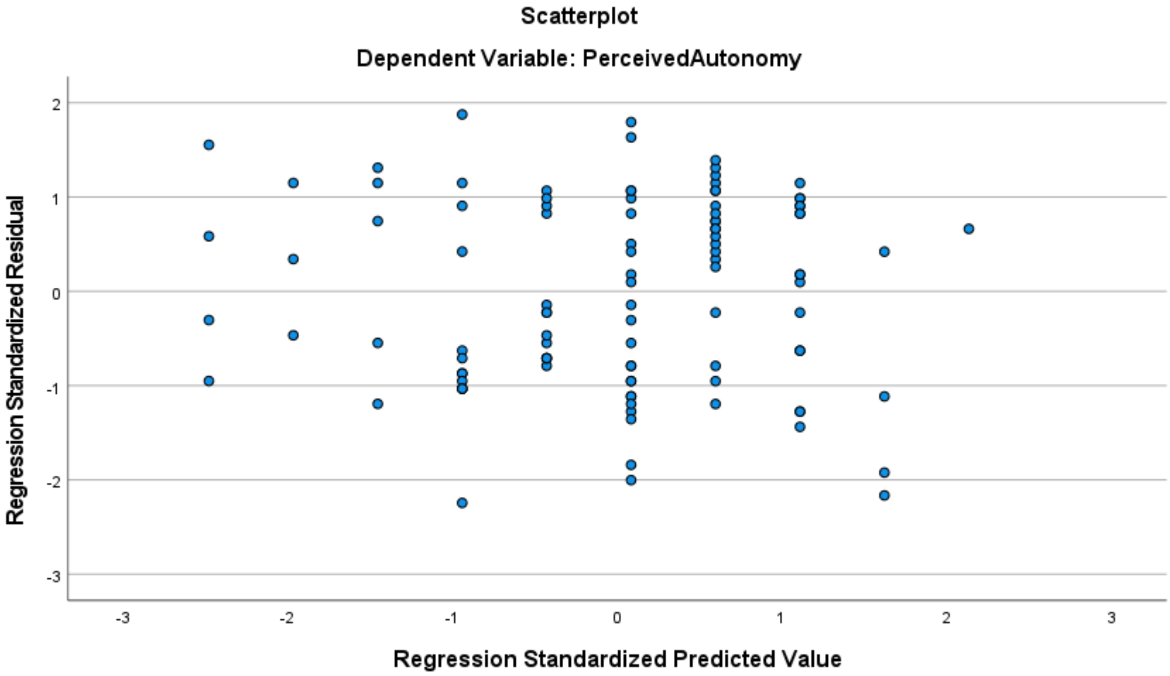
Perceived autonomy & Masculinity:



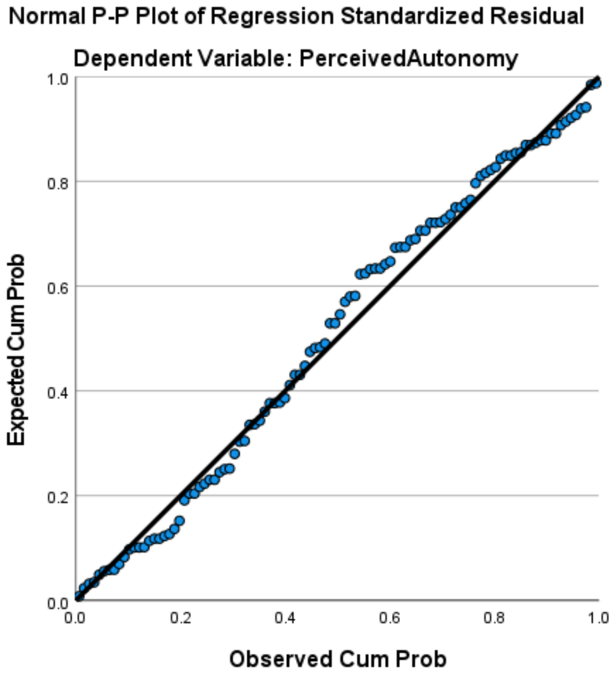


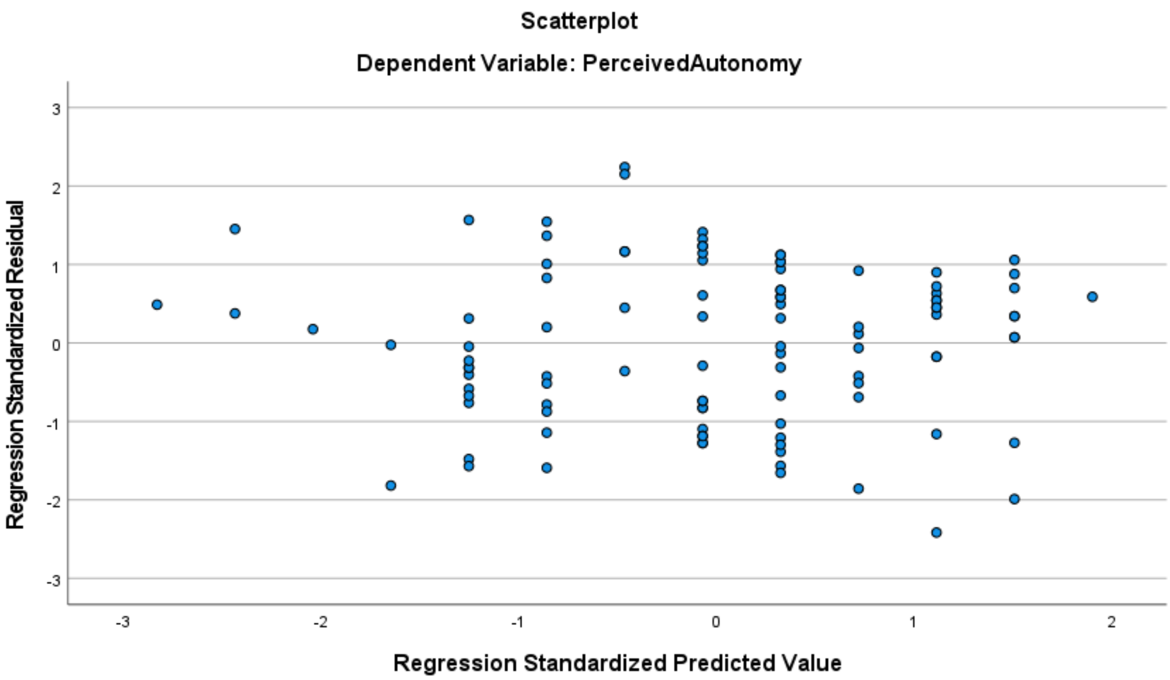
Perceived autonomy & Uncertainty Avoidance:



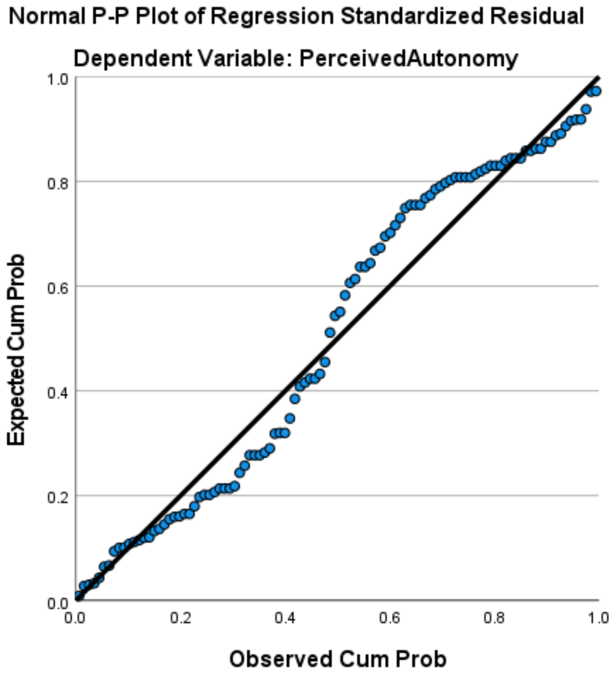


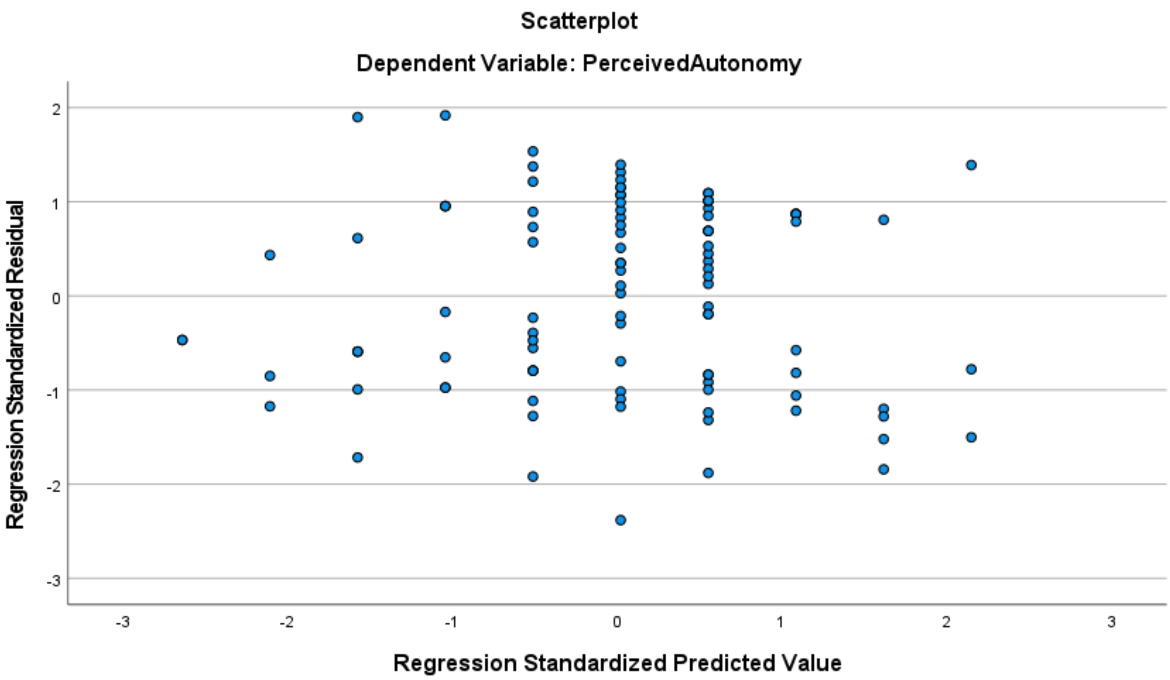
Perceived autonomy & Long Term Orientation:





Perceived autonomy & Indulgence:


Normal P-P Plot of Regression Standardized Residual
Dependent Variable: PerceivedAutonomy
Expected Cum Prob
Observed Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0


Scatterplot
Dependent Variable: PerceivedAutonomy
Regression Standardized Residual
Regression Standardized Predicted Value
-3
-2
-1
0
1
2
3

Appendix S - Regression (PA) - ANOVA

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.027	1	5.027	4.826	.030[b]
	Residual	106.241	102	1.042		
	Total	111.268	103			

a. Dependent Variable: PerceivedAutonomy

b. Predictors: (Constant), NewPowerDistance

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	19.190	1	19.190	21.257	.000[b]
	Residual	92.078	102	.903		
	Total	111.268	103			

a. Dependent Variable: PerceivedAutonomy

b. Predictors: (Constant), Individualism

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	18.977	1	18.977	20.973	.000[b]
	Residual	92.291	102	.905		
	Total	111.268	103			

a. Dependent Variable: PerceivedAutonomy

b. Predictors: (Constant), Masculinity

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.741	1	2.741	2.576	.112[b]
	Residual	108.527	102	1.064		
	Total	111.268	103			

a. Dependent Variable: PerceivedAutonomy

b. Predictors: (Constant), NewUncertaintyAvoidance

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	23.100	1	23.100	26.724	.000[b]
	Residual	88.168	102	.864		
	Total	111.268	103			

a. Dependent Variable: PerceivedAutonomy

b. Predictors: (Constant), LongTermOrientation

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.469	1	1.469	1.365	.245[b]
	Residual	109.799	102	1.076		
	Total	111.268	103			

a. Dependent Variable: PerceivedAutonomy

b. Predictors: (Constant), NewIndulgence

Appendix T - Regression (PA) - Model Summary

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.213[a]	.045	.036	1.02058

a. Predictors: (Constant), NewPowerDistance

b. Dependent Variable: PerceivedAutonomy

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.415[a]	.172	.164	.95012

a. Predictors: (Constant), Individualism

b. Dependent Variable: PerceivedAutonomy

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.413[a]	.171	.162	.95122

a. Predictors: (Constant), Masculinity

b. Dependent Variable: PerceivedAutonomy

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.157[a]	.025	.015	1.03150

a. Predictors: (Constant), NewUncertaintyAvoidance

b. Dependent Variable: PerceivedAutonomy

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.456[a]	.208	.200	.92973

a. Predictors: (Constant), LongTermOrientation

b. Dependent Variable: PerceivedAutonomy

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.115[a]	.013	.004	1.03753

a. Predictors: (Constant), NewIndulgence

b. Dependent Variable: PerceivedAutonomy

Appendix U - Regression (PA) - Coefficients

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	3.851	.593		6.496	.000	2.675	5.027					
	NewPowerDistance	.345	.157	.213	2.197	.030	.034	.657	.213	.213	.213	1.000	1.000

a. Dependent Variable: PerceivedAutonomy

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	2.330	.615		3.786	.000	1.109	3.551					
	Individualism	.692	.150	.415	4.611	.000	.394	.989	.415	.415	.415	1.000	1.000

a. Dependent Variable: PerceivedAutonomy

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	2.610	.559		4.669	.000	1.501	3.719					
	Masculinity	.624	.136	.413	4.580	.000	.354	.895	.413	.413	.413	1.000	1.000

a. Dependent Variable: PerceivedAutonomy

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	4.229	.573		7.375	.000	3.091	5.366					
	NewUncertaintyAvoidance	.251	.156	.157	1.605	.112	-.059	.561	.157	.157	.157	1.000	1.000

a. Dependent Variable: PerceivedAutonomy

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	2.302	.555		4.145	.000	1.200	3.404					
	LongTermOrientation	.747	.144	.456	5.169	.000	.460	1.033	.456	.456	.456	1.000	1.000

a. Dependent Variable: PerceivedAutonomy

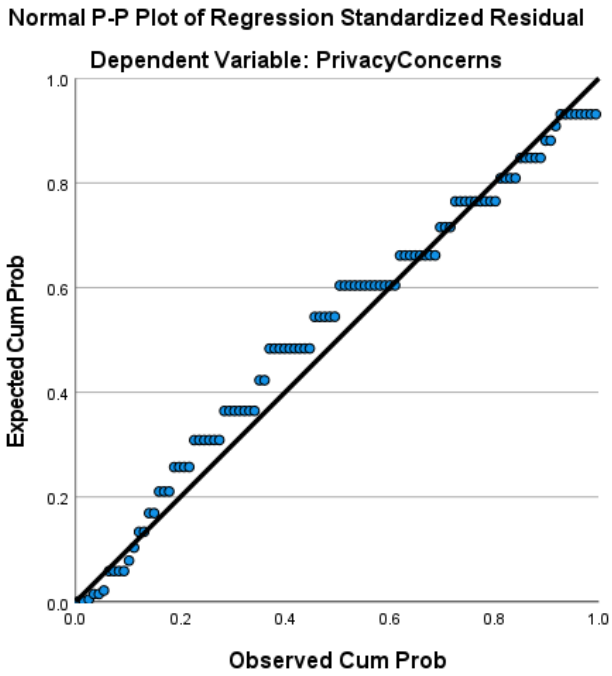
Coefficients[a]

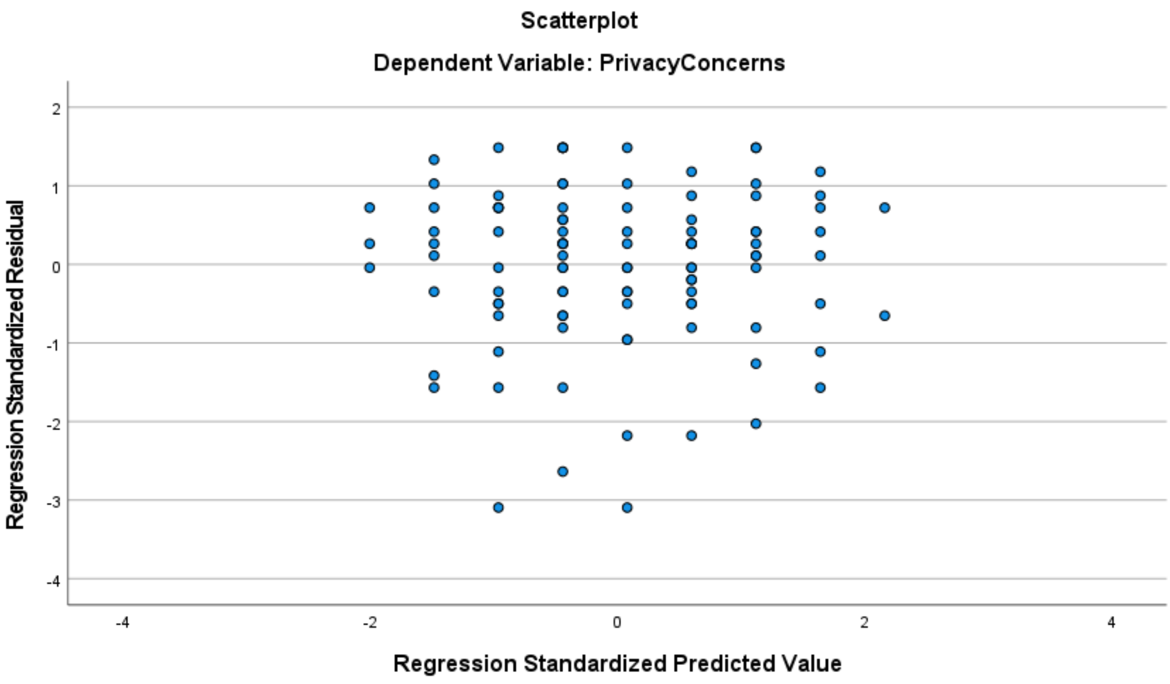
Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	4.438	.605		7.337	.000	3.238	5.638					
	NewIndulgence	.191	.163	.115	1.168	.245	-.133	.514	.115	.115	.115	1.000	1.000

a. Dependent Variable: PerceivedAutonomy

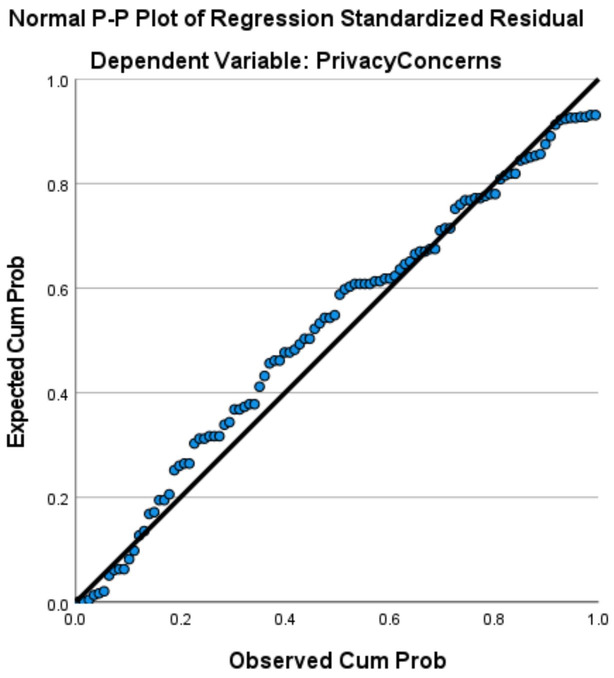
Appendix V - Checking assumptions (DV: Privacy Concerns)

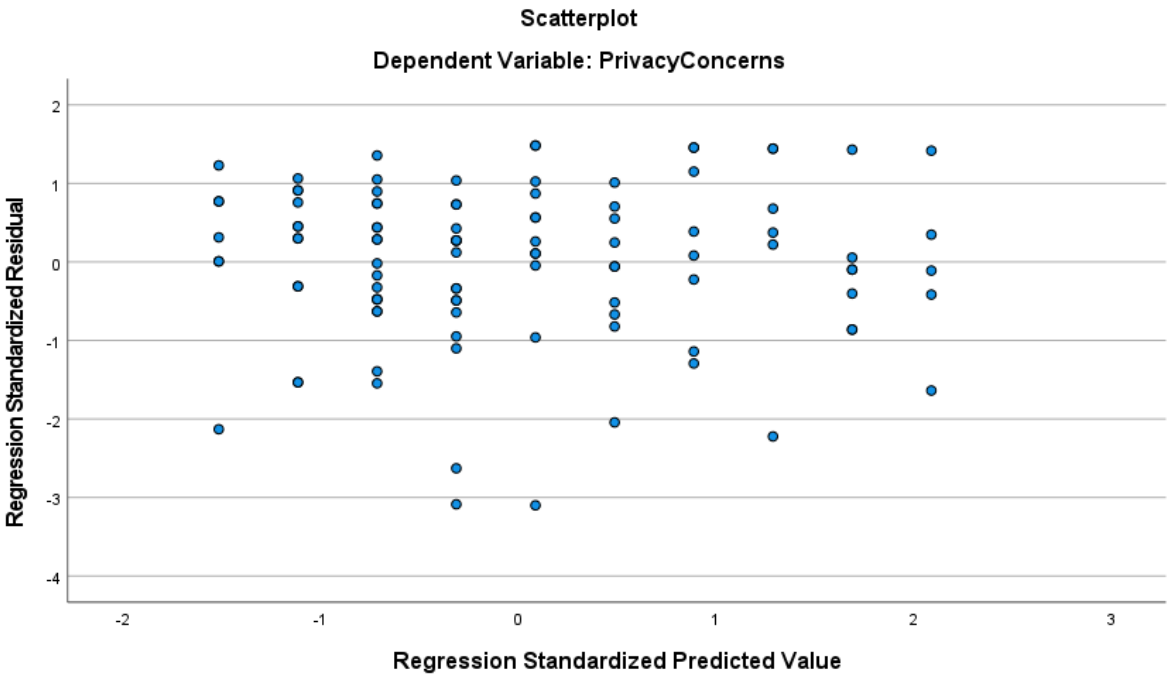
Privacy Concerns & Power Distance:



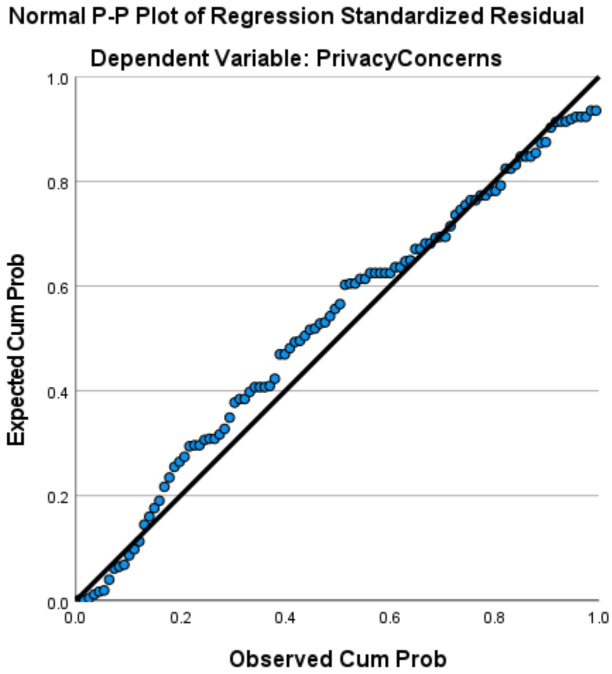


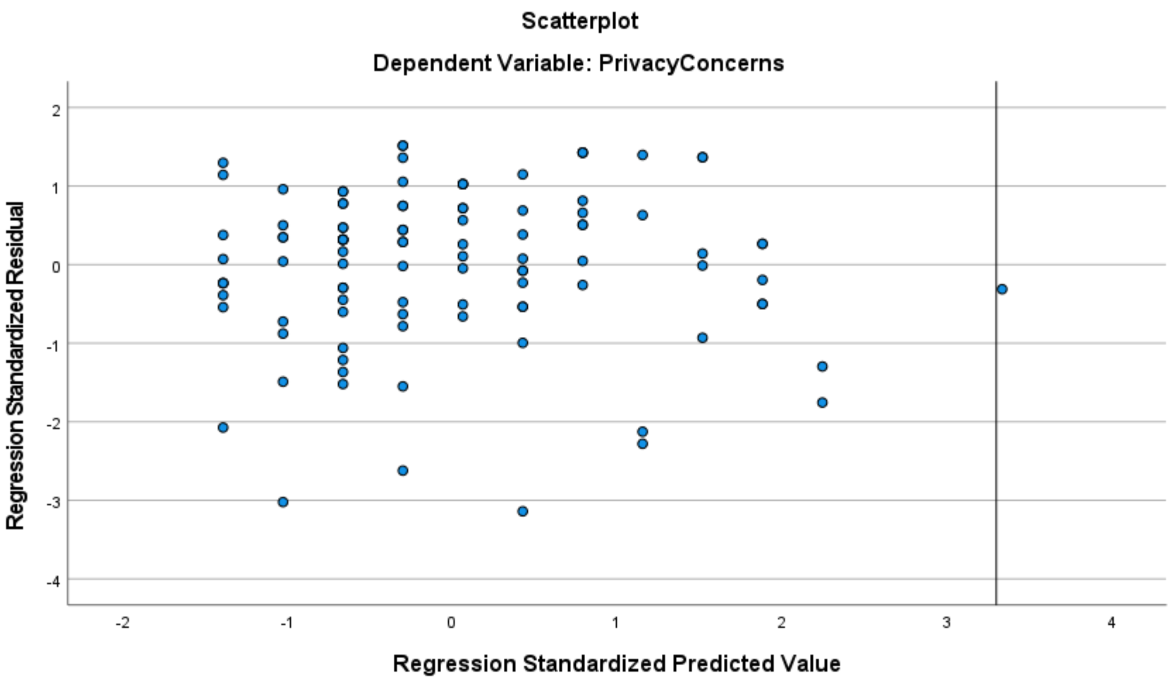
Privacy Concerns & Individualism:



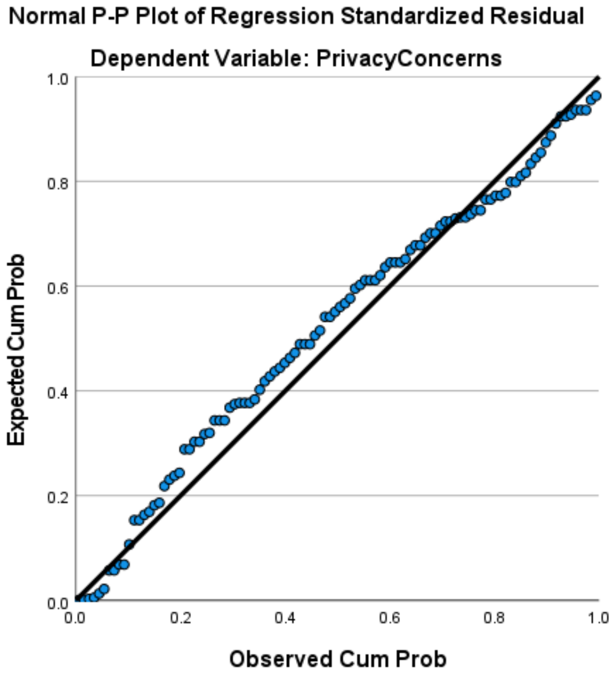


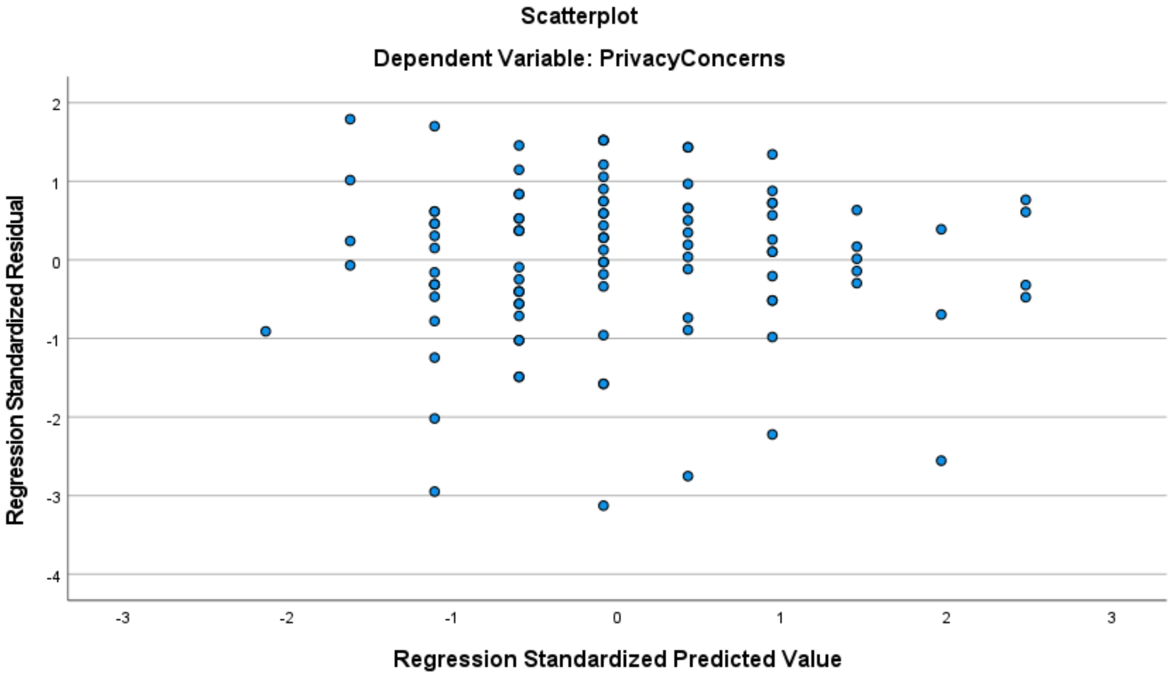
Privacy Concerns & Masculinity:



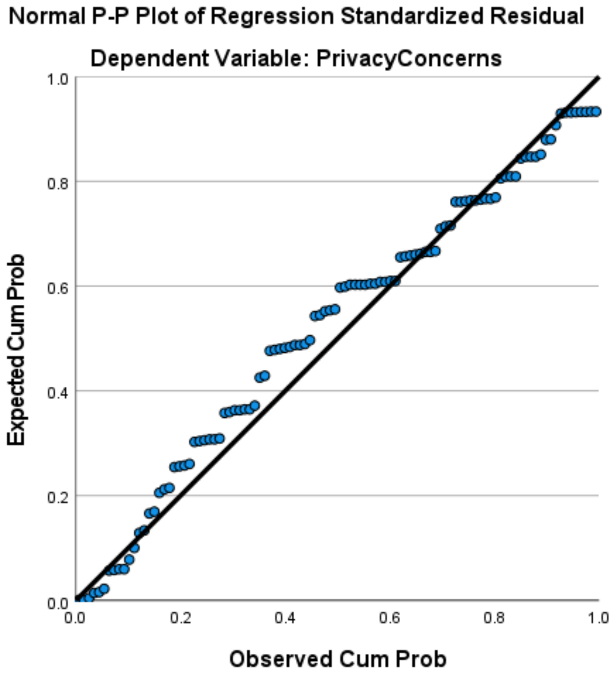


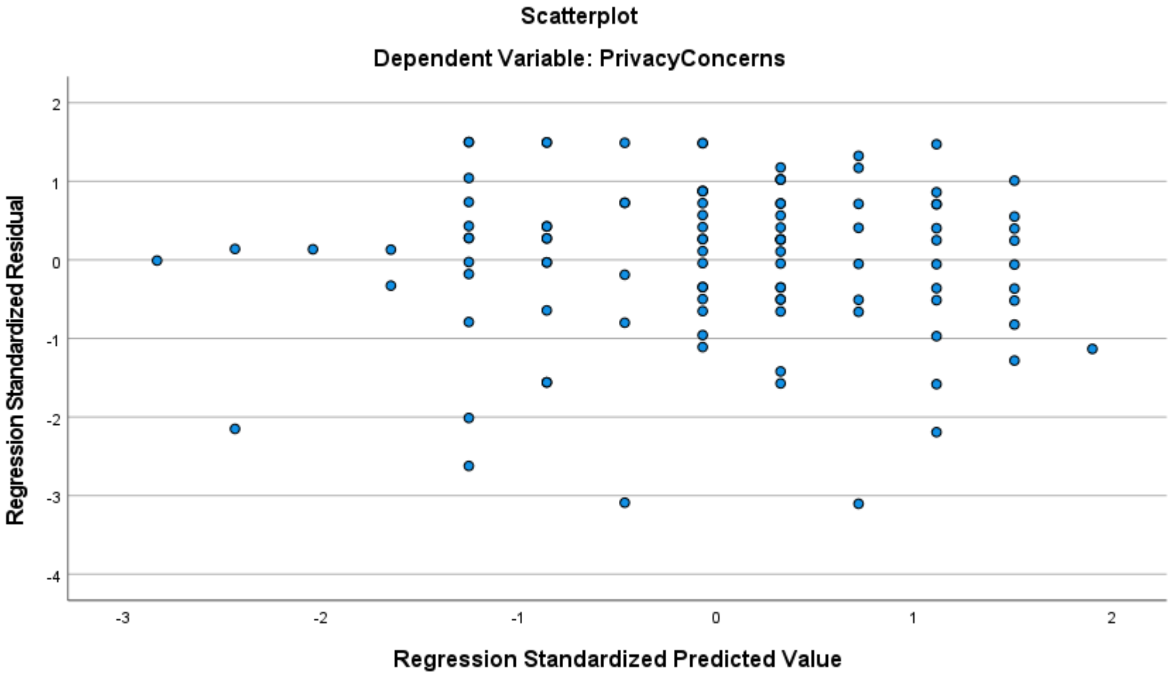
Privacy Concerns & Uncertainty Avoidance:



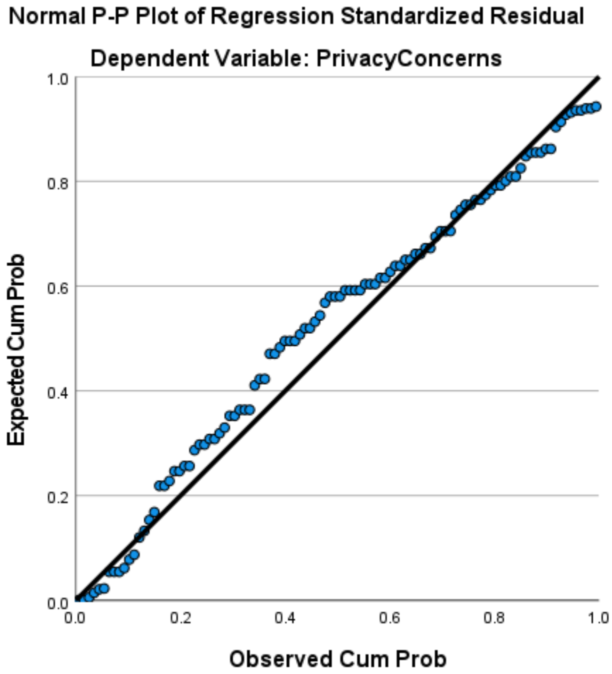


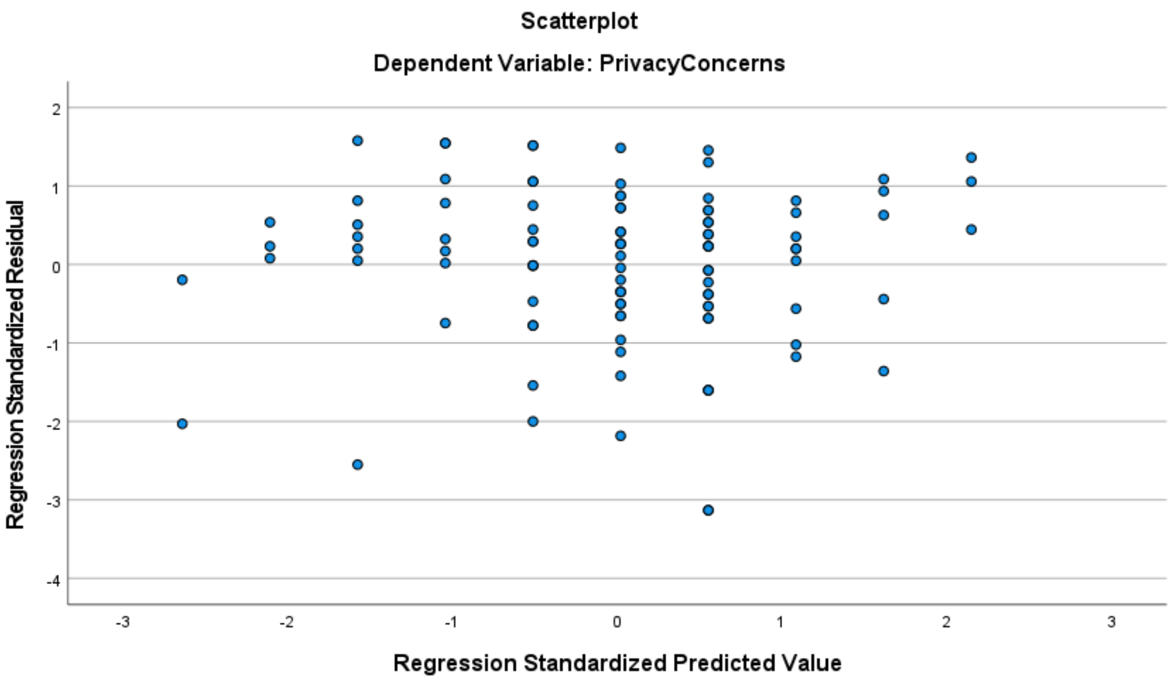
Privacy Concerns & Long Term Orientation:





Privacy Concerns & Indulgence:


Normal P-P Plot of Regression Standardized Residual
Dependent Variable: PrivacyConcerns
Expected Cum Prob
Observed Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0


Scatterplot
Dependent Variable: PrivacyConcerns
Regression Standardized Residual
Regression Standardized Predicted Value
2
1
0
-1
-2
-3
-4
3

Appendix W - Regression (PC) - ANOVA

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.000	1	.000	.000	.998[b]
	Residual	175.058	102	1.716		
	Total	175.058	103			

a. Dependent Variable: PrivacyConcerns

b. Predictors: (Constant), NewPowerDistance

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.190	1	.190	.111	.740[b]
	Residual	174.869	102	1.714		
	Total	175.058	103			

a. Dependent Variable: PrivacyConcerns

b. Predictors: (Constant), Individualism

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.153	1	1.153	.676	.413[b]
	Residual	173.905	102	1.705		
	Total	175.058	103			

a. Dependent Variable: PrivacyConcerns

b. Predictors: (Constant), Masculinity

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.228	1	5.228	3.140	.079[b]
	Residual	169.830	102	1.665		
	Total	175.058	103			

a. Dependent Variable: PrivacyConcerns

b. Predictors: (Constant), NewUncertaintyAvoidance

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.025	1	.025	.014	.905[b]
	Residual	175.034	102	1.716		
	Total	175.058	103			

a. Dependent Variable: PrivacyConcerns

b. Predictors: (Constant), LongTermOrientation

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.587	1	.587	.343	.559[b]
	Residual	174.471	102	1.711		
	Total	175.058	103			

a. Dependent Variable: PrivacyConcerns

b. Predictors: (Constant), NewIndulgence

Appendix X - Regression (PC) - Model Summary

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.000[a]	.000	-.010	1.31006

a. Predictors: (Constant), NewPowerDistance

b. Dependent Variable: PrivacyConcerns

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.033[a]	.001	-.009	1.30935

a. Predictors: (Constant), Individualism

b. Dependent Variable: PrivacyConcerns

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.081[a]	.007	-.003	1.30574

a. Predictors: (Constant), Masculinity

b. Dependent Variable: PrivacyConcerns

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.173[a]	.030	.020	1.29035

a. Predictors: (Constant), NewUncertaintyAvoidance

b. Dependent Variable: PrivacyConcerns

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.012[a]	.000	-.010	1.30997

a. Predictors: (Constant), LongTermOrientation

b. Dependent Variable: PrivacyConcerns

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.058[a]	.003	-.006	1.30786

a. Predictors: (Constant), NewIndulgence

b. Dependent Variable: PrivacyConcerns

Appendix Y - Survey questions

Survey variable	*Measure*	*Reference*
Power Distance 2+7: 1. of utmost importance 2. very important 3. of moderate importance 4. of little importance 5. of very little or no importance 20+23: 1. strongly agree 2. agree 3. undecided 4. disagree 5. strongly disagree	2. have a boss (direct superior) you can respect (1 = PD) 7. be consulted by your boss in decisions involving your work (1 = PD) 20. How often, in your experience, are subordinates afraid to contradict their boss (or students, their teacher?) (1 = PD) 23. An organization structure in which certain subordinates have two bosses should be avoided at all cost (1=PD)	Hofstede & Minkov, 2013

Individualism vs Collectivism 1. of utmost importance 2. very important 3. of moderate importance 4. of little importance 5. of very little or no importance	1. have sufficient time for your personal or home life 4. have security of employment 6. do work that is interesting 9. have a job respected by your family and friends	Hofstede & Minkov, 2013
Masculinity vs Femininity 1. of utmost importance 2. very important 3. of moderate importance 4. of little importance 5. of very little or no importance	3. get recognition for good performance (1 = MAS) 5. have pleasant people to work with 8. live in a desirable area 10. have chances for promotion	Hofstede & Minkov, 2013

Uncertainty Avoidance 15: 1. always, 2. usually 3. sometimes 4. seldom 5. never 18: 1. very good 2. good 3. fair 4. poor 5. very poor 21+24: 1. strongly agree 2. agree 3. undecided, 4. disagree 5. strongly disagree	15. How often do you feel nervous or tense? 18. All in all, how would you describe your state of health these days? 21. One can be a good manager without having a precise answer to every question that a subordinate may raise about his or her work 24. A company's or organization's rules should not be broken - not even when the employee thinks breaking the rule would be in the organization's best interest	Hofstede & Minkov, 2013
Long Term Orientation 13+14: 1. of utmost importance 2. very important 3. of moderate importance 4. of little importance 5. of very little or no importance 19: 1. very proud, 2. fairly proud, 3. somewhat proud 4. not very proud	13. doing a service to a friend 14. thrift (not spending more than needed) 19. How proud are you to be a citizen of your country? 22. Persistent efforts are the surest way to results	Hofstede & Minkov, 2013

5. not proud at all 22: 1. strongly agree 2. agree 3. undecided, 4. disagree 5. strongly disagree		
Indulgence vs Restraint 11+12: 1. of utmost importance 2. very important 3. of moderate importance 4. of little importance 5. of very little or no importance 16+17: 1. always, 2. usually 3. sometimes 4. seldom 5. never	11. keeping time free for fun 12. moderation: having few desires 16. Are you a happy person? 17. Do other people or circumstances ever prevent you from doing what you really want to?	Hofstede & Minkov, 2013

Perceived autonomy Likert scale 1-7 1. Strongly agree 3. Somewhat agree 5. Somewhat disagree 7. Strongly disagree	1. I feel a sense of choice and freedom in the choice I made 2. I feel that my decision reflected what I really want 3. I feel my choice expresses who I really am 4. I feel I chose what really interests me 5. Choosing made me feel like ‘‘I had to’’ 6. I felt forced to make a choice which I normally wouldn’t do 7. I felt pressured to make the choice 8. Making a choice felt like an obligation 9. I felt in control of my choice 10. I felt that my choices belonged to me 11. My choice reflected my preferences 12. The choice I made were free from external influence	Haugstulen, 2021: Chen et al., 2015: Michaelsen et al., 2021

Privacy concern 1. Very concerned 3. Slightly concerned 5. Slightly unconcerned 7. Very unconcerned	1. How concerned would you be about your online personal privacy? 2. How concerned are you about disclosing your financial information? 3. How concerned would you be that your personal data may be used for purposes other than the reason you provided the information for? 4. How concerned would you be about the fact that sites you visited might be known/tracked? 5. How concerned would you be about your personal information being shared with other parties?	Wirtz et al., 2007: Haugstulen, 2021
Conjoint analysis variable	*Measure*	*Reference*
ACA autonomy	(High level) You choose freely which car insurance company you want. (Medium level) You choose freely between 5 different car insurance companies (Low level) The car loan requires you to pick their recommended car insurance company	

ACA privacy	(High level) Personal information given: damage history, estimated mileage, place of residence, demographics. GPS tracks: where and how much you are driving, speed limit violations, sharp braking/accelerating/turns. (Medium level) Personal information given: damage history, estimated mileage, place of residence, demographics. (Low level) Personal information given: damage history and estimated mileage.	
Price	3000 NOK, 2000 NOK, 1000 NOK	
Discount	15%, 30%,45%	
Preference for artificial intelligence	(High) Any potential insurance settlements calculated by artificial intelligence	

	(Low) Any potential insurance settlements calculated by humans.	

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Science and Technology