The Role of Consumers' Knowledge in Battery Electric Vehicle Diffusion

A Study of the Norwegian Battery Electric Vehicle Advancement Through Structural Equation Modelling

By

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Preface

The basis for this research originally stemmed from my passion of understanding consumer behaviour, as well as a strong interest in green solutions aiming to create a sustainable future. I would like to thank my supervisors and board members for supporting my research, giving constructive feedback as well as being understanding of hurdles along thy way. Lastly, I'd like to state that the author is responsible for all contents while Delft University of Technology is solely responsible for the educational coaching and are not liable for its content.

A. Pettersen
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Abstract

Battery electric vehicles (BEVs) are considered an important contribution to the global task of creating a greener society as it allows for the benefits of commuting to sustain, without the consequence of pollution. Consequently, central and local governments across the globe are attempting to spark the diffusion of BEVs through various measures such as financial incentives, developing charging networks or other distinctive benefits. In this process, understanding and exploring the factors which affect consumers to transition from Internal Combustion Engine Vehicles (ICEVs) to BEVs is essential for the salient actors attempting to increase the adoption rates. In this thesis, we aim to add to this branch of BEV research by investigating the factors influencing consumers' adoption intention of BEVs while introducing the element of consumers' BEV knowledge and familiarity.

To analyse these effects, a conceptual structural model based on an extended Technology Acceptance Model (TAM) was developed and analysed. The conceptual model involved a total of eight variables: Consumer's knowledge, risk perception, perceived usefulness, attitude towards BEVs, BEV incentives, incentive awareness, intention to adopt a BEV, and the side-by-side comparison to ICEVs as a vehicle alternative. The model was then empirically tested through an extensive questionnaire survey involving data from 266 consumers in the BEV pioneer Norway. To collect this data, the researcher utilized a combination of snow-ball and convenience sampling where the survey was spread through online platforms. Further, the data was analysed through Structural Equation Modelling (SEM) in the software IBM SPSS AMOS to determine the validity of the conceptual model as well as the effect among the variables.

To evaluate the results, a Confirmatory Factor Analysis (CFA) was performed. The results of this analysis indicated that the conceptual model was a good fit despite its complexity. In regard to consumer's knowledge, the analysis indicated that there was a strong and significant total effect on the adoption intention of BEVs. More specifically, knowledge functioned as a strong predictor through mediating effects of increased perceived usefulness, improved attitude and reduced risk perception related to BEVs. In addition, Knowledge was found to have a strong and significant positive total effect on the mentioned side-by-side "comparison to ICEVs" variable. Further, through a separate regression analysis, the results also revealed the knowledge variables was found to have an explained variance of .3 in regard to the "intention to adopt" variable. This was significantly higher than any other variable in the analysis. Further, the analysis showed that perceived risks could be a considerable psychological barrier against accepting and adopting BEVs. This barrier, however, was significantly reduced in accordance with increasing levels of consumers' BEV knowledge. Lastly among the SEM key findings, attitude towards BEVs was found to have the strongest direct effect on adoption intention in the model. A variable which again was found to be strongly positively influenced by consumer's knowledge about the vehicles.

The descriptive statistics of the analysis also found noteworthy characteristics in the sample population. For instance, the data revealed that the average knowledge and familiarity levels among the population were as high as 5.82 on the 7-point Likert scale used in the survey research. In combination with the discovered effect of knowledge (on "intention to adopt" and "comparison to ICEV"), this finding could indicate that high levels of BEV knowledge might be an important contributor to Norway's disproportionately large adoption rates compared to that of other salient actors. One should be cautious, however, to draw this conclusion without performing a similar study in a comparable setting and location. Further, the statistics revealed an average score of 6.29/7 on the variable measuring the awareness of the governmental incentives in Norway. This is another strong sign that the country has succeeded in spreading information on the topic among its population. Another interesting finding in this regard was the low satisfactory levels with the Norwegian charging networks. With an average score of 3.62/7 (SD=1.57) among the sample, it is clear that a large part of the respondents are dissatisfied with the charging infrastructure. However, the low satisfactory levels does not seem to have a large impact on the intention to adopt BEVs as there was found no significant effect among these variables.

A demographic regression analysis with the independent variables of gender, age and education on the dependent variable “intention to adopt” was also performed. This revealed that both gender and education had a small, yet significant effect on the dependent variable where men and high education was associated with higher adoption intentions. Age on the other hand, had no significant effect.

In sum, the main takeaway from this study is that consumers’ knowledge of BEVs should be taken into consideration when attempting to manage the adoption of the green vehicles. Norway has succeeded in diffusing knowledge of BEVs and fiscal incentives within its population, and this might be part of the explanation for their disproportionally large adoption rates compared to other salient actors. The recommendation based on the results in this research is therefore that governments aiming to substitute ICEVs with BEVs should take measures to spread information and educate potential adopters on BEVs and its technology. Achieving this would improve the overall attitude towards BEVs, increase the perceived usefulness and limit the existing risk barriers. In turn, this would increase consumers’ willingness to adopt BEVs and contribute to the global task of creating a greener society.

1 Understanding The Diffusion of Battery Electric Vehicles

As society acknowledges the consequences of continuously increasing emissions and rapid climate change, several industries are currently experiencing a green shift with the shared goal of creating a sustainable future. Consequently, the automobile industry is transitioning towards low or non-polluting alternatives which has led to an increased market share of Battery Electric Vehicles (BEVs) in recent years (EV-VOLUMES, 2019). This transition could lead to great emission reductions as BEVs don't produce greenhouse gas emission when driven. Further, the vehicles have the ability to run solely on clean energy, making it an important contribution to a greener society (Granovskii, Dincer, & Rosen, 2006). In addition, moving away from internal combustion engine vehicles (ICEVs) would lead to improved air quality, particularly in urban areas, reducing the health risks involved with the increasingly polluted air (European Enviroment Agency, 2019).

However, despite the expanding diffusion, BEVs currently only accounts for a small fraction of the automobile market (EV-VOLUMES, 2019). This can partly be explained by the BEV features which are inferior to those of ICEVs, such as limited driving range, longer refuelling time and dependency on charging networks (She, Qing Sun, Ma, & Xie, 2017). These factors, combined with perceived high investment costs, fear of battery replacement costs and perceived risks, are assumed to be the key barriers against a large scale BEV diffusion (Junquera, Moreno, & Álvarez, 2016; Steinhilber, Wells, & Thankappan, 2013; Wiedmann, Hennigs, Pankalla, Kassubek, & Seegebarth, 2011).

On the other hand, BEVs also provides direct benefits to consumers on top of the positive environmental impacts. This includes significantly lower fuel running costs, reduced maintenance costs, safety improvements and higher torque engines (Hagman, Ritzén, Stier, & Susilo, 2016). In addition, central and local governments, particularly in Europe, the United States and China, are issuing fiscal policies to reduce the influence of the barriers and hence spark the diffusion of BEVs. This includes financial and non-financial consumer incentives, charging network development and rebates to counter the investment cost. The incentives, however, are highly varying among the actors both in nature and impact, making it challenging to design effective policies to spark the electrical automobile transition (Sierzchula, Bakker, Maat, & van Wee, 2014).

Perhaps the most pertinent subject when investigating these factors is that of the Scandinavian BEV pioneer Norway. The country is arguably the only one to successfully introduce BEVs to the automobile market so far, with an adoption rate of approximately 50% in the first quarter of 2019, and 31% in the year of 2018 (E24, 2019). Compared to other key actors aiming to take part in the transition, like the Netherlands, Germany or the UK, this accounts for around 10 times the adoption rates in corresponding timeframes (Bovag, 2019; European Enviroment Agency, 2018).

The general explanation for the Norwegian success with BEV diffusion is that their governments over the past three decades have issued impactful incentives which are larger in magnitude than that over other actors (Tietge, Mock, Lutsey, & Campestrini, 2016). The measures involve financial advantages of registration tax exemption (1990), reduced annual vehicle license fee (1996) and VAT exemption (2001). In addition, indirect or non-financial measures of free toll (1997), free parking in certain regions (1999) and reduced ferry rates (2009) has been issued (Pfaffenbichler, Fearnley, Figenbaum, & Jellinek, 2015). As a result, the incentives has led several BEVs to have a lower Total Cost of Ownership (TCO) in a pairwise comparison to comparable ICEVs (Lévay, Drossinos, & Thiel, 2017).

When reviewing this list of incentives and TCO analysis, it is understandable that Norway has reached higher adoption rates than that of other countries with weaker incentives. However, it is difficult to grasp that adoption rates are more than 10 times higher than other proactive countries due to this factor alone. Especially when digging deeper into the practical aspects which are known to function as barriers against BEV diffusion. For instance, with Norway's large land area (385 000 km^2), very low population density (14/km^2) and highly spread population, the limited driving range is consequently a considerable issue for conventional use (Trading Economics, 2019). Further, the cold climate of the northern country causes issues and limitations to BEVs battery capacity several months of the year due to low temperatures (Lindgren & Lund, 2016).

To emphasize this further, one could compare all of the abovementioned factors with the other salient actor Netherlands, which also practices a set of incentives such as low registration tax, ownership tax exemption and free parking in certain areas (Tietge et al., 2016). Similarly to Norway, these incentives have led certain BEVs to have a lower TCO than that of comparable ICEVs (though less frequent and lower in magnitude) (Lévay et al., 2017). Further, the Benelux country possesses a near perfect geographical environment to limit range anxiety through a warmer climate, small land area and high population density (417/km^2). In addition, to deal with range anxiety and other perceived inconvenience, the country has developed one of the world's most dense charging networks with over 18,500 public and 17,000 semi-public charging points as of September 2018. This makes up an astonishing 0.6 fully public charging points per registered passenger BEV (Netherlands Enterprice Agency, 2018). In comparison, this is a significant improvement from the Norwegian network which is under pressure with its 0.08 charging points per registered BEV (Statistisk Sentralbyra, 2017). By taking all these factors into consideration, it's conceivable that other factors could play a role in the diffusion and the massive differences in adoption rates.

To understand these factors affecting diffusion is particularly valuable to policymakers attempting to shape a greener society through the transition, making it an important research topic overall. In the literature reviewed in chapter 2, it was found that considerable effort has been put into this branch of research in recent years. The common approach in the research on the topic, is to relate the governmentally issued incentives to the adoption rates, and then evaluate their effectiveness based on this correlation. Another utilized approach to study the phenomena is to map consumers' opinion on factors of BEVs which differs from ICEVs, such as driving range limitations, charging networks, charging time, purchase prices and fiscal incentives. In short, this research has led to updated beliefs concerning the influencing factors and contributed to the decision-making process for policymakers worldwide. The previous research has also revealed that these correlations are inconsistent, partly complex and dependent on location and context. In this sense, it appears that there is still a lot to be understood and other potential factors to consider about what influences BEV diffusion, such as in the case of the disproportionate advancements in Norway.

There are, however, examples of studies which has utilized alternative approaches and aimed to investigate other influencing external factors in BEV diffusion. In 2018, a study was published through the University of Science and Technology of China by Shanyong Wang and his team of researchers in the renewable energy sector. Their research aimed to investigate whether BEV knowledge among consumers influences the purchase intentions among the Chinese population. The results, after communicating with 320 potential automobile customers, questioned aspects of what was previously assumed about BEV diffusion. First and foremost, they found a significant relationship between knowledge and purchase intentions. Further, knowledge was found to be associated with significantly lower risk perceptions as well as improving consumers overall attitude towards BEVs and its technology. Lastly, their quantitative survey study was not able to find any significant relationship between consumers adoption intentions and issued fiscal incentives in China (Wang, Wang, Li, Wang, & Liang, 2018)

Several factors such as culture, environment, and magnitude of incentives make it challenging to generalize these results to other countries. For instance, it is already known that incentives have played a significant role in BEV diffusion in Norway as previously discussed. However, the effect of knowledge on the adoption could possibly be an unaddressed factor in the massive diffusion in the last decade. Norway already began to address the issue of transitioning towards BEVs in the 1990s, and the technology has received large amounts attention, particularly in the media, for several years (Pfaffenbichler et al., 2015). Therefore, it is plausible that the general BEV knowledge in the Norwegian population is higher than that of other salient actors. Hence, if the results regarding knowledge's influence from Wang et al. are generalizable to Europe, it would be part of the explanation for the massive adoption rates.

In this project, we aim to research this phenomenon by using inspiration from the study by wang et al. to investigate the factors influencing consumers adoption intentions and acceptance of BEV technology by introducing the factor of consumers BEV knowledge and familiarity. Hence, as the behavioural intention is believed to be the most direct antecedent of actual behaviour, the study attempts to understand knowledge's role in the diffusion (Ajzen & Gilbert Cote, 2008). Further, the study is conducted in Norway, with the overall theory that high levels of BEV knowledge and familiarity among the Norwegian public functions as a key driver in the successful diffusion. By using the Scandinavian country as a model, we hope to better understand the factor of knowledge in consumers acceptance and purchase intentions of BEVs. Hence, the overall research question of the project is framed as follows:

"How do consumers' knowledge of battery electric vehicles influence the intention to purchase the vehicles?"

In addition to the overall research question, the study aims to answer a set of sub-questions rooted in the literature study in chapter 2 which relates to the overall objective.

- Firslty, as we know from previous research that financial and non-financial incentives has a positive effect on diffusion (see chapter 2.3), we want to investigate the importance of knowledge in comparison to the incentives. Hence sub-question 1 reads as follows:
  SQ1- How does the factor of knowledge compare to the other key factors of governmental incentives and charging network on the intention to adopt BEVs?
- Previous research has indicated that risk perception related to BEVs functions as a significant barrier against diffusion (see chapter 2.4). To be able to include this factor in the research, the second sub-question reads:
  SQ2- How does risk perceived with BEVs influence consumers intention to adopt BEVs?
- The main purpose of assessing the influence of risk perception as a diffusion barrier in SQ2 relates to the next sub-question. Here, we wish to investigate whether consumers' knowledge affects the risk perception.
  SQ3- How does knowledge affect the risk perception of investing in BEVs among consumers?
- Further, as discribed in chapter 2.2.1, the framework of the study is based on an extended Technology Acceptance Model developed by Fred Davis. This model involves variables of percivced usefilness and attitude which are known to infleunce the intention to use new technologies. In line with the overall research question, sub-quaestion 4 reads as follows:
  SQ4- How does BEV knowledge influence the general perception of the vehicles in terms of attitude and degree of usefulness?
- Lastly, the study aims to investigate consumers' perception of the strict comparison between BEVs and ICEVs as two directly competing vehicle alternatives. In other words, not concerning the role of incetives and other issued distinctive benefits. Further, we wish to investigate the infleunce of knowledge on this comparison.
  SQ5- How does knowledge of BEVs influence the perceived comparison between BEVs and ICEVs as a standalone vehicle alternative?

The report starts off by reviewing previous research on BEV diffusion and knowledge's role in consumer theory used to develop theories on what to expect (chapter 2). From there, the research framework and related hypothesis is presented in chapter 3. The next chapter describes the methodology involved in performing the study, as well as the measures to perform the analysis and the data collection procedure. Chapter 5 presents the results from the analysis, followed by chapter 6 where the findings are discussed and a conclusion to the research questions is presented.

2 Previous Research on BEV Diffusion and Knowledge in Consumer Theory

In this chapter, the previous literature on diffusing BEVs will be reviewed. First, the root of the study, namely the role of knowledge in consumer behaviour, will be examined. The chapter then proceeds by discussing diffusion of BEVs as a technology aiming to replace ICEV technology. The third part of the literature study examines the previous research on diffusion through governmental incentives, followed by the role of risk perception in diffusion. The literature review was done exclusively through online databases. The Scientific journals was found in Scopus and Scholar, while other sources was found through online searches.

2.1 The Influence of Consumers’ Knowledge and Familiarity

Here, the influence of knowledge on consumer behaviour will be discussed. Firstly from the perspective of behavioural economics in general. The chapter then proceeds to investigate the influence of BEV knowledge in the automobile market specifically.

2.1.1 Knowledge and Consumer Behaviour

The level of knowledge and familiarity has been a part of behavioural research for decades and is considered to have an important role in the decision-making process of consumers. Generally, studies indicate that knowledge of a product increases the likelihood of a consumer making a purchase. The relationship is often explained by knowledge having both a direct and indirect effect on purchase intention. This involves reducing risk perception in conjunction with purchases, properly assessing an alternative, or influencing a consumer’s attitude towards a product (Kaplan, 1991; Ogbeide, 2015).

Particularly on the subject of energy-saving and environmentally friendly products, research has found that knowledge improves consumers attitude and increases the willingness to pay. This phenomenon has been investigated on several occasions, for instance by Hong-Youl Ha at Kangwon National University in South Korea in 2012. His research on predicting consumer intentions discovered that consumer’s knowledge about energy-saving products had a positive impact on their attitude towards the product. Further, he found that attitude then had a very strong and significant effect on purchase intention. In other words, the results revealed that knowledge was particularly influential on purchase intention in this product segment through improving the attitude as a mediating effect (Ha, 2012).

Another example of this was revealed through a major study conducted in Crete by the Reginal Energy Agency of Crete, where Nikolas Zafrafakis and his team aimed to assess the willingness to pay for renewable energy sources. The study involved a face-to-face interview with 1440 households and made interesting findings regarding renewable solutions. Their results revealed, among others, that knowledge about the sources significantly increased the willingness to pay among the Greek consumers (Zografakis et al., 2010). As BEVs has the ability to recharge run solely on renewable energy, this could indicate that the same effect might exist in the BEV industry.

Similarly, research has been conducted on consumer familiarity and its influence on consumer behaviour. A publication from Magnus Soderlund at Stockholm School of Economics, found that pre-purchase familiarity with a product had several effects on consumer behaviour. Not only did it increase the purchase intentions, but it also increased the word-of-mouth intentions among those experiencing high familiarity (Söderlund, 2002).

Lastly, knowledge of new technologies through accumulating information is theorised to be among the key elements in the process of adopting new technologies (Feder & Slade, 1984). As BEVs are not just a competing product in the car market, but a competing technology, it's important to view the adoption from this perspective as well. This perspective is further discussed in chapter 2.2.

2.1.2 Previous research on Knowledge's Effect on BEV Adoption

The previous research on this particular phenomena is scarce, where the 2018 publication by Shanyong Wang et al., which was discussed in the introduction remains a key contributor. Their study was conducted with the purpose of investigating the role of consumers knowledge on BEV diffusion in comparison to other factors. The quantitative study involved 320 potential adopters with a wide range in demographics spread across 10 Chinese cities. Their results questioned previous assumptions about the diffusion and concluded that knowledge was highly influential on consumers adoption intentions. They further found several mediating effects caused by increased knowledge, such as a decrease in risk perception, which is considered a diffusion barrier. Overall their study indicated that knowledge as a factor might be overlooked and underestimated in the attempts of sparking the diffusion (Wang et al., 2018).

There are few other publications with this specific objective, but a survey study performed by the Consumer Federation of America (CFA) in 2015 made similar findings when mapping American consumer's knowledge on BEVs. When commenting on the findings, CFA's Director of Research Mark Cooper stated "Our research shows a clear, statistically significant, correlation between knowledge about BEVs and positive attitudes towards BEVs. The more one knows about BEVs, the more positive one feels about these vehicles. Furthermore, there is a statistically significant correlation between positive attitudes about BEVs and a willingness to purchase them—those who feel positively about BEVs are more likely to consider purchasing one," (Consumer Federation of America, 2015). In other words, there was a statistically significant correlation between the public's knowledge about BEVs and the adoption intention. It should be noted that this study was more linear and simplistic than that of Shanyong Wang, and did not concern other factors or mediating effects.

Apart from these studies there have been few other attempts to investigate the influence of knowledge on adoption intention. Particularly in Europe, where many governments actively attempt to influence the adoption of the new vehicles, a major study of this nature was not found. This provides an excellent opportunity to undergo studies to fill this gap in BEV diffusion research.

2.2 Analysing BEV Diffusion as a Competing Technology

So far in this chapter, BEVs are referred to as a product which competes in the vehicle market. However, the diffusion of BEVs can also be viewed as diffusion of a "new" technology which aims to replace the currently dominating technology of ICEVs. Different from more classical "technology battles", is that BEVs are not aiming to replace an inferior performing technology. It aims to replace a technology which first and foremost causes problems in society through pollution. Nevertheless, it's interesting to review the literature on the adoption of new technologies with this perspective in mind.

In the process of analysing BEV diffusion as a competing technology, various models are available. The choice of method in this research fell on the popular Technology Acceptance Model (TAM) which was first introduced by Fred Davis in 1989 (Davis, Bagozzi, & R. Warshaw, 1989). The TAM was first and foremost chosen because the inspiration study led by Wang implemented the model with success. Other reasons were the flexibility it offers through the ability to make modifications and add external variables to the model. As well as that the model has managed to stay relevant and still functions as a tool to generate acceptance to important technologies today (Marangunić & Granić, 2015; Nadri, Rahimi, Lotfnezhad Afshar, Samadbeik, & Garavand, 2018). A description of the TAM can be found I chapter 3.1.

2.3 The Role of Incentives in BEV Diffusion

In this chapter, previous research on the influence of BEV incentives will be discussed with extra attention to the country of Norway as it is the target of this study.

2.3.1 Effectiveness of Financial Incentives

Researching the effects of financial incentives on BEV adoption is a popularized subject in recent years as it is valuable information when governments develop soft policies to cause a voluntary transition away from ICEVs. The studies, however, often gives conflicting answers when it comes to the effectiveness and efficiencies of the issued policies, and they appear to be dependent on context and location.

A suitable example of this phenomena can be found in the beforementioned study from China, one of the world leaders on BEV diffusion. In addition to the discoveries related to knowledge, Shandong Wang and his team concluded, based on their findings, that "the current financial incentive policy has no significant effect on adoption intention in China" (Wang et al., 2018). Contradictory, Shao-Chao Ma et al. at China University of Petroleum, came to the opposite conclusion when evaluating the national issued financial incentives in China. They concluded that subsidies and tax exceptions had in fact been successful and would have a positive impact on the diffusion in both the short and long term (Ma, Fan, & Feng, 2017). What is important to take note of is that these studies took a different research approach. Wang et al. studied the effect by communicating with a large set of consumers, asking about the impacts of incentives on their intention to purchase BEVs. While Ma et al. took the approach of comparing the adoption rate with issued incentives over a period of 66 months leading up to November 2017.

In Europe, the studies are more accordant in terms of the correlation between financial incentives and BEV adoption, but the effectiveness is often locally dependent. In 2016 The International Council on Clean Transportation (ICCT) issued a report where they compared the effect of fiscal incentives issued in Europe's five largest EV markets. The study concluded that the direct financial incentives were the most important driver for the uptake, particularly in Norway and Germany. For the three other countries (UK, France and The Netherlands) the fiscal incentives were less influential, indicating that other factors must be considered as significant factors on EV adoption (Tietge et al., 2016).

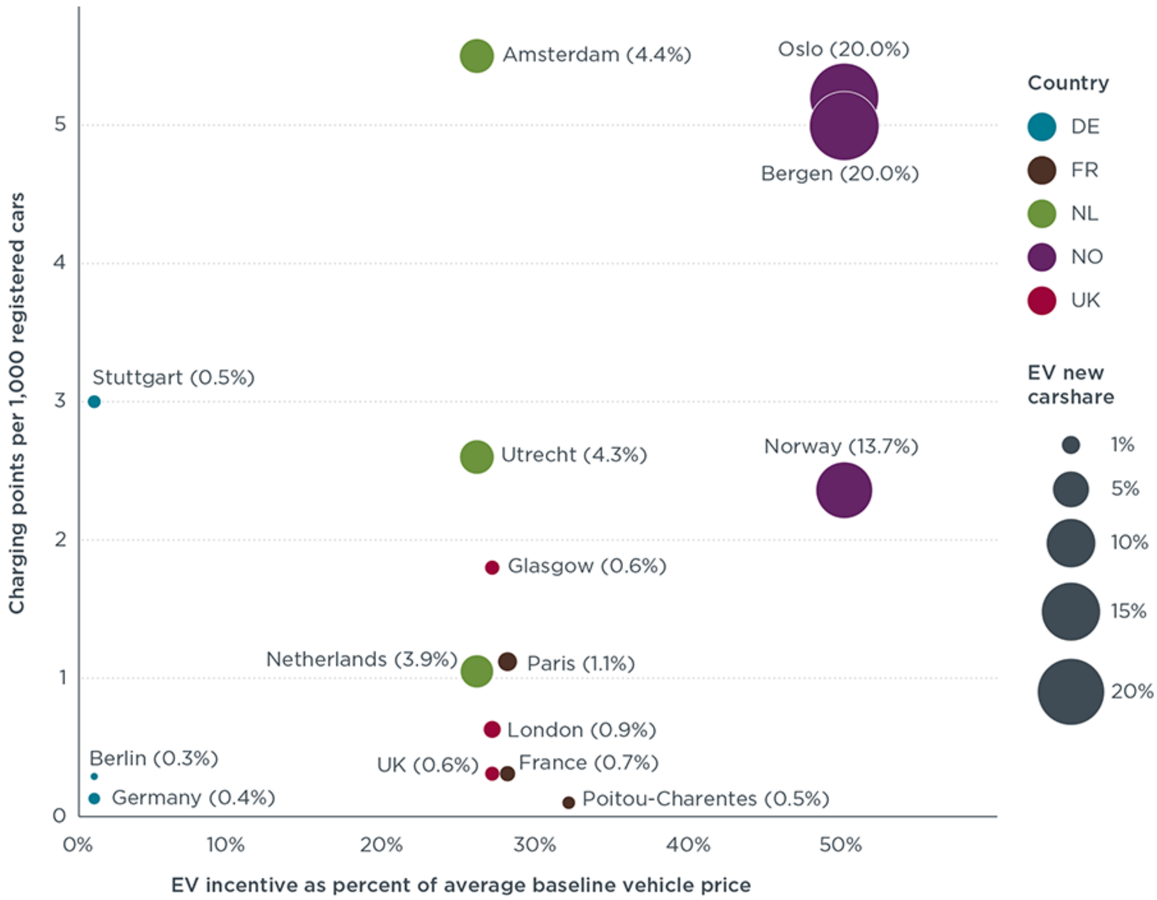

Figure 1. ICCTs Plot of fiscal incentives for BEVs and charging point density for five European countries and 10 cities/regions. The size of the marker represents the EV share of newly registered vehicles in 2014 (Tietge et al., 2016).

A more recent study from 2017 by Scott Hardman et al. at the University of California made an extensive review of the evidence of incentives' effectiveness through aggregate and disaggregate data based in the nine biggest BEV markets. The report concluded that "Due to the abundance of literature using diverse methodologies this literature review can confidently state that BEV incentives are an effective policy measure in increasing BEV sales", adding to the consensus that there exists a significant effect. The study did however also point out that the effectiveness of each incentive is not currently known, and that other factors should be considered, such as personal motivations and measures to raise awareness (Hardman, Chandan, Tal, & Turrentine, 2017).

2.3.2 Impact of Non-Financial Incentives and Charging Networks

In addition to the financially motivated fiscal policies, several governments (particularly in China, Europe and the US) have also issued a set of non-financial incentives to spark the BEV diffusion. This includes measures to develop charging networks, free parking, access to bus lanes during peak hours, free charging stations. The effectiveness of these incentives is less frequently researched as they are difficult to measure and compare across countries.

However, there are studies which attempts to determine its influence. The abovementioned report by The International Council on Clean Transportation showed that non-financial incentives within their research's scope had a smaller, yet not insignificant effect in adoption compared to the financially motivated incentives. They found that in Bergen, Oslo, Utrecht, and California, local incentives had led to a superior adoption rate compared to the national average. They did however also point out that this effect might be due to raised consumer awareness in these regions, which again could have been triggered by the same regional non-financial incentives. Lastly, they found that countries with dense charging networks had higher BEV market shares overall (See figure 2). However, no conclusions were made in terms of the direction of this chicken and egg situation. In other words, even though they found the two factors to be correlated, they could not conclude that developing charging networks would directly lead to increased BEV diffusion (Tietge et al., 2016).

Another interesting finding was made by the Norwegian Centre for Transportation Research in 2015, where the organization evaluated non-financial incentives overall, paying extra attention to Norway and Austria. They found that certain non-financial incentives issued in Norway, particularly the free-parking for BEVs policy had little effect on adoption and were considered the least cost-effective among the measures. Further, the incentive of access to bus lanes was considered to have a positive, but cost ineffective relation with the diffusion in Norway. On the other hand, the same measure was far less effective in Austria (Pfaffenbichler et al., 2015). This further strengthens the theory of locally dependent effectiveness of incentives.

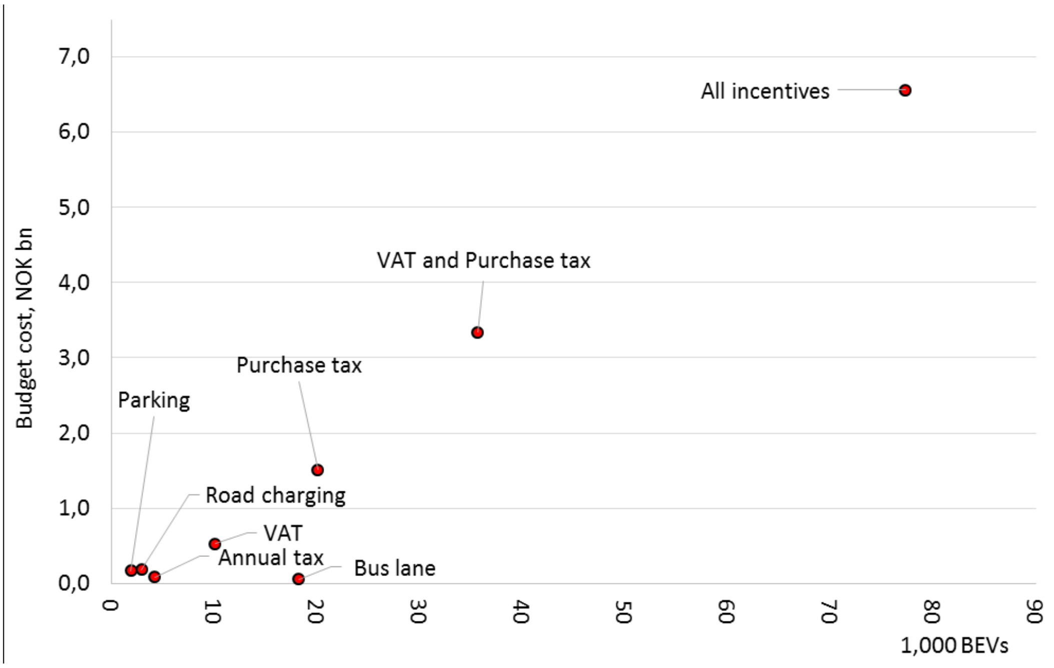

Figure 2. Incentives' efficiencies (Pfaffenbichler et al., 2015).

In other parts of the world, such as Korea, the effectiveness of non-financial incentives appears to be less influential. A study by Moon-Koo Kim et al. at the Korea Advanced Institute of Science and Technology gave some interesting results. By collecting data from 285 drivers in Korea, they were not able to find any correlation between non-financial incentives and intention to adopt BEVs. Hence, they concluded that “only financial incentives enhanced the relationship between value perception and adoption intention”, which supports the theory that the effect of non-financial incentives are uncertain and highly dependent on where they are issued (Kim, Oh, Park, & Joo, 2018).

2.4 Risk Perception as a Barrier

BEVs have key features which differs from ICEVs such as recharging rather than refuelling, shorter range and an overall different technology. As a result, different risks for the consumers are also involved. As with new technologies in general, studies show that consumers have a lower risk tolerance than with existing alternatives, making potential adopters extra sensitive to perceived risks related to the vehicles (Stoneman & Diederen, 1994). Further, studies has revealed that the phenomena of risk perception as a diffusion barrier is present when dealing with renewable energy solutions. For instance, Eunil Park and Jay Ohm found that increased perception of risks decreases the attitude towards the technology solutions as well as the intention to use it (Park & Ohm, 2014). The automotive sector is no exception, where sustainable solutions involves several types of risks which functions as a barrier against adoption (Wiedmann et al., 2011). Primarily this involves risks related to:

- Performance: The risk of the vehicle not performing as well as it's alternative. When dealing with BEVs this concerns acceleration, handling, range, comfort and other aspects which the alternatives might differ. Studies indicate that the average consumer is not likely to accept compromises in performance in exchange for cleaner technology (Heffner, Kurani, & Turrentine, 2005).
- Time: This involves the risk of losing time due to the recharging procedure and range limitations.
- Finances: Consumers may associate financial risks with making a purchase due to the high investment costs, battery replacement costs and other potential financial losses (Junquera et al., 2016). In addition, consumers perception of the payback time due to lower fuel running costs affects these financial risks.
- Physical harm: The last of the most relevant risks involved are those of physical harm, e.g. driver, passenger and external personal safety, which might be perceived different than with ICEVs.

How consumers perceive the above-mentioned risks are important to the consumers' willingness to adopt (Wiedmann et al., 2011).

2.5 Main Findings Through Literature Study

- Knowledge of a product prior to a purchase has been found to positively influence the purchase intention on several occasions.
- Particularly when dealing with "green" and innovative products, knowledge is considered to have a positive effect as it improves the overall attitude towards the product or technology.
- Product familiarity is found to increase the word-of-mouth intention, thus giving an additional positive effect.
- There have been few attempts to investigating the role of consumer's knowledge in the BEV industry specifically, but a study from China in 2018 found a significant relationship with the intention to purchase.
- Accumulating knowledge is considered a key element in the adoption of new technologies trying to get a foothold in the market.
- According to the reviewed research, financially motivated incentives are the most effective measure when actors aim to increase the adoption rates of BEVs. They are, however, different in effect depending on where they have been issued. The strongest sign of their effect is in Norway, where their governments have issued intensive incentives for three decades.
- The effect of non-financial incentives are subject to more uncertainty where several measures are found to be highly cost-ineffective.
- Particularly when dealing with new and innovative technologies, consumers' perception of risks related to purchasing the product is a significant barrier as the risk tolerance is lower.
- In the automotive industry, the risks to consider are related to performance, time, finances and physical harm.
- An extended version of Davis' Technology Acceptance Model was found to be the most appropriate methodology to analyse the BEV diffusion in line with the studies' objective.

3 Hypothesis and Research Framework

Based on the research objective in chapter 1 and literature study in chapter 2, a research framework was developed in the form of a conceptual causal model. The model consists of the factors expected to influence consumers perception and adoption intention of BEVs, and their interrelated effects. The model is based on the Technology Acceptance Model (TAM) mentioned in chapter 2, extended to fit the purpose of our study. The model is also inspired by the framework described by Shanyong Wang et al. with certain modifications. In this chapter, the TAM is presented, followed by the utilized variables in our framework. The chapter proceeds by presenting the hypothesised effects between the variables based on the literature study. Chapter 3 is then completed by presenting the overall conceptual model with all variables and hypothesized effects.

3.1 The Technology Acceptance Model

Fred Davis' TAM was firstly introducing in 1989 and builds on a set of independent and dependent variables which aims to explain the factors influencing users adoption decisions when facing new technologies (systems). The TAM has continuously been studied and expanded after its release. However, the underlying core principles of the original model is still used in today's models. The original model is presented in the following figure. (Davis et al., 1989).

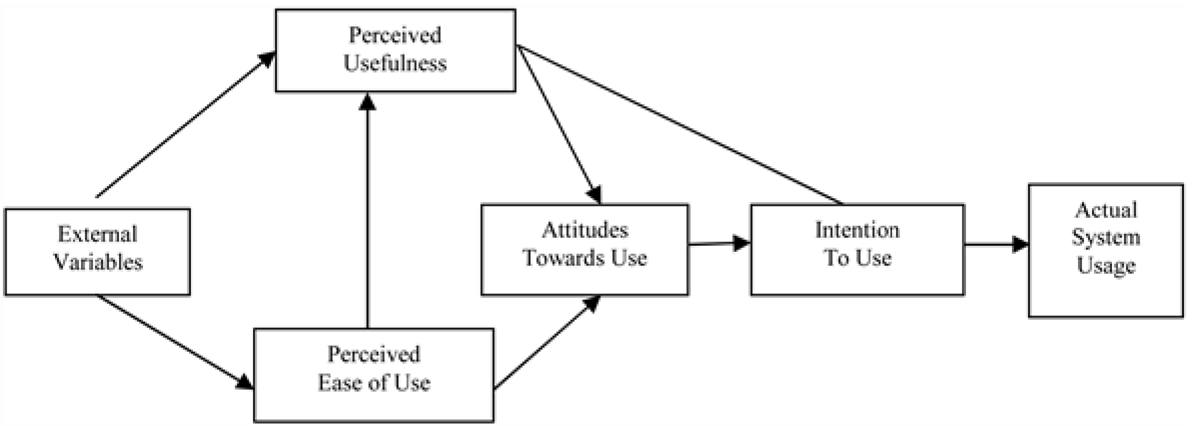

Figure 3. Davis' original TAM (Davis et al., 1989).

The model instigates from the left with a set of *external independent variables*, which are context-dependent in terms of which technology is analysed. These variables then influence the following psychological variables:

Perceived usefulness, which is defined by Davis as "the degree to which a person believes that using a particular system would enhance his or her job performance". As the original model concerned Computer systems, the definition is narrow and does not concern the extended use of the model after its publication. The definition is therefore modified to the technology it is analysing. The variable is still considered an important mediator in technology diffusion today and is frequently used in more recently developed TAMs (Marangunić & Granić, 2015).

Perceived ease of use, defined by Davies as "the degree to which a person believes that using a particular system would be free from effort". This is the most controversial variable in the TAM. The main cause of the criticism revolves around the dilemma of whether potential adopters can have a justified perception of "ease of use" of a technology they have not previously tested. In addition, studies have suggested that the perceived ease of use does not significantly influence technology adoption in several cases (TGE, 2019).

Further, the psychological variables affect the *attitude* towards use, defined as “an individual’s positive or negative feelings (evaluative affect) about performing the target behaviour”. This is a crucial variable which directly influences the intention to use the technology in the model. The variable is still an essential part of TAMs and has been illustrated to be among the strongest predictors of intended behaviour like discussed previously in the chapter.
The model is then completed with the sequential variables of *indented* and *actual use* which are closely related, yet often found to be different in magnitude (Ajzen & Gilbert Cote, 2008).

The TAM was first and foremost chosen because the inspiration study led by Wang implemented the model with success. Other reasons were the flexibility it offers through the ability to make modifications and add external variables to the model. As well as that the model has managed to stay relevant and still functions as a tool to generate acceptance to important technologies today. The variables and framework in the next sub-chapter is based on the foundation of this model with added context dependent external variables based on the literature study and project’s objective.

3.2 The Variables in the Framework

In total, eight variables were included in the research framework and developed hypothesis. The core of the model’s variables are drawn from the original TAM, while the remaining variables are developed in line with the research objective and literature study. In this sub-chapter, the variables are defined as well as elaborated in terms of the factors to consider when determining the variables.

Knowledge of BEVs (KB). This is the key predictor in the model as it introduces an element which is rarely considered when researching BEV diffusion. The variable refers to how knowledgeable and familiar the potential adaptors are with BEVs in terms of performance, usage, costs etc.

Perceived risks (PR). As described in chapter 2.4, perceived risk is considered to function as a barrier against diffusion. Hence, to include this dimension in the framework, this variable measures the consumer's perception of risks related to adopting BEVs. The risk is a multi-dimensional variable which includes risks of physical harm, financial risks, and risks related to practicalities such as the limited driving range, charging networks and recharging time (Li, Long, Chen, & Geng, 2017; Wiedmann et al., 2011).

Perceived usefulness (PU). This variable is directly adopted from Davis’ original TAM described above. In this context, the usefulness refers to how useful consumers find the BEVs as a whole in terms of a measure to reduce emissions, improve air quality and a transportation alternative.

Attitude towards BEVs (AB). This variable is as well as “perceived usefulness” based on the original TAM. As described through the literature study, this is believed to be a crucial part when influencing consumers in green energy sectors. The variable refers to the attitude in terms of interest in BEVs, opinion of the overall technology as a green alternative, and whether adopting is a good decision overall.

Intention to Adopt BEVs (IA). This is the final variable adopted from the original TAM and concerns the intention to adopt/purchase a BEV among the potential adopters. As intention to purchase is believed to be among the strongest indicators of actual purchases, this variable could function as a predictor for BEV adoption (Ajzen & Gilbert Cote, 2008).

Incentive Policies (IP). This concerns the incentive policies and charging networks as perceived by the consumers. It determines the satisfactory levels and perception of incentives and charging networks in the population.

Awareness of Incentives (AI). The model’s final predictor is also a unique feature as of research frameworks in BEV diffusion research. The AI measures whether the public is aware of the issued incentives and developed charging networks.

Comparison to ICEVs (CI). The final variable in the framework is another unique feature of the model. The variable concerns the perceived comparison between BEVs and ICEVs in terms of performance, risks and value. It is implemented in the model because it, unlike the "intention to adopt", does not concern the role of incentives and other issued distinctive benefits. In other words, it describes a direct comparison of two alternative types of vehicles on the market. On the other hand the "intention to adopt" might be caused by incentives, and not by one alternative being perceived as better than the other.

3.3 Hypothesis and Construction of Conceptual Model

Through the literature study and logical reasoning, a hypothesis was developed in form of effects between the developed variables. The hypothesized effects and their reasoning is explained in this chapter, whereas the visual presentation of the conceptual framework is presented in chapter 3.4.

Knowledge of BEVs (KB). *Based* on the literature review, this is hypothesised to reduce the perception of risks related to BEVs and hence have a negative effect on perceived risks. Further, based on what was found in chapter 2.1 and what is known about the TAM, it is hypothesised to have a positive effect on the perceived usefulness, attitude, adoption intention and comparison to ICEVs. More specifically, as knowledge is hypothesised to have a positive effect on the intention to adopt (and perceived comparison to ICEVs), it should have positive mediating effects in line with the TAM on usefulness and attitude.

KB→Perceived Risks (-)
KB→Perceived Usefulness (+)
KB→Attitude towards BEVs (+)
KB→Intention to Adopt BEVs (+)
KB→Comparison to ICEVs (+)

Perceived risks (PR). As discussed in chapter 2.4, perceived risks are assumed to be a barrier when it comes to adopting BEVs as a technology (Oliver & Rosen, 2010; Qian & Yin, 2017). Hence, in line with the TAM, increased perceived risks are assumed to have a negative effect on perceived usefulness and attitude, as well as the intention to adopt and the side-by-side comparison with ICEVs.

PR→ Perceived Usefulness (-)
PR→ Attitude towards BEVs (-)
PR→ Intention to Adopt (-)
PR→ Comparison to ICEVs (-)

Perceived usefulness (PU). In line with Davis' TAM, the perceived usefulness is assumed to positively influence the attitude, adoption intention and consequently comparison to ICEVs. (Davis, 1989)

PU→ Attitude towards BEVs (+)
PU→ Intention to Adopt (+)
PU→ Comparison to ICEVs (+)

Attitude towards BEVs (AB). Similarly, based on the TAM and previous literature, the attitude towards BEVs is believed to be strongly related to adoption intention and comparison variables.

AB→ Intention to Adopt (+)
AB→ Comparison to ICEVs (+)

Incentive Policies (IP). As discussed in chapter 2, the research on incentive policies does give conflicting results in terms of their effectiveness. However, the general consensus is that they have a positive effect on adoption rates and is, therefore, hypotheses to positively affect the intention to adopt.

IP→ Intention to Adopt (+)

Awareness of Incentives (AI). Similarly to IP, the level of awareness of incentives are hypothesised to positively relate to the adoption intentions.

AI→ Intention to Adopt (+)

3.4 Illustration of Conceptual Research Framework

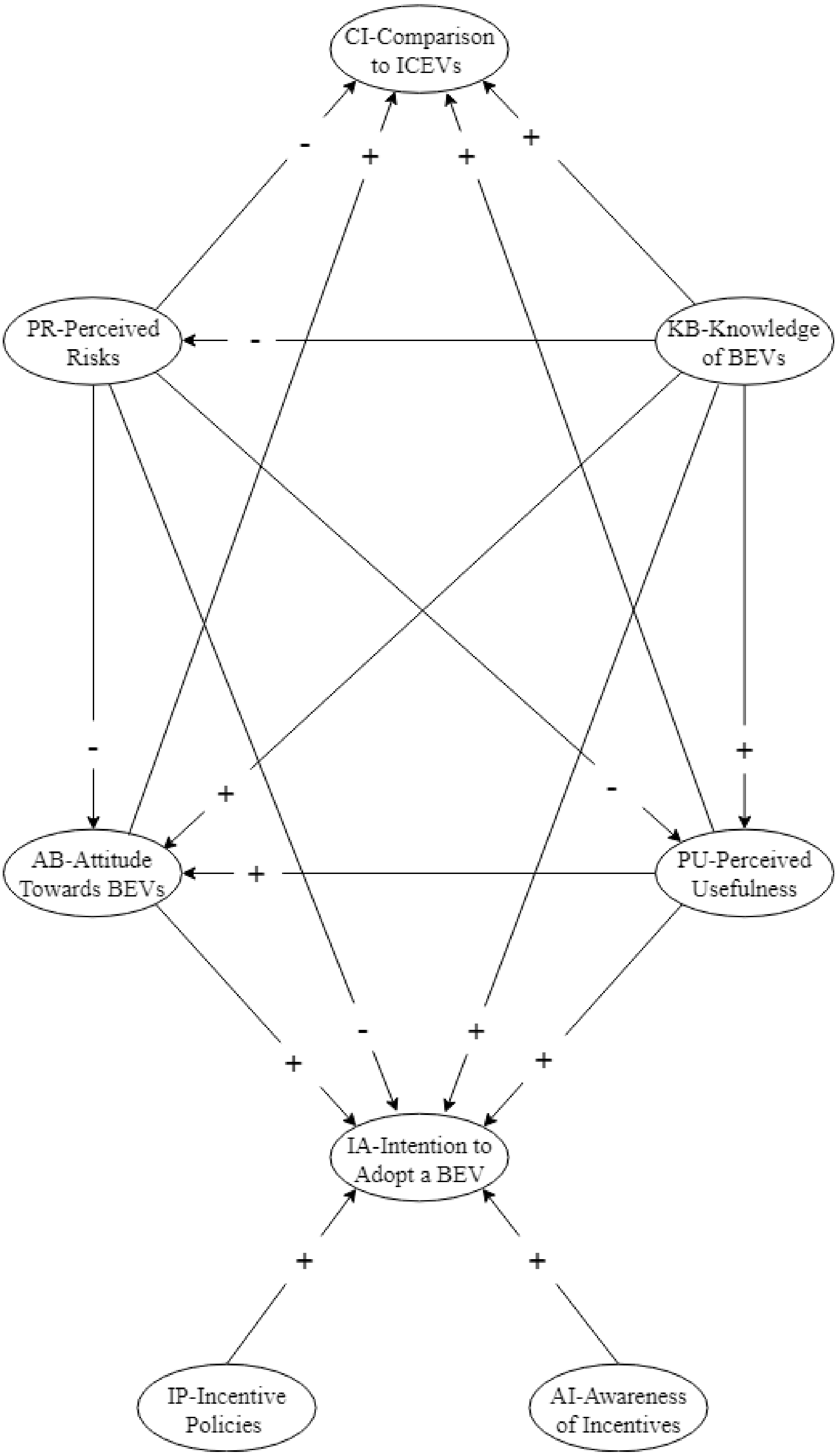

Figure 4. Original conceptual model

4 Methodology and Measures

4.1 Applied Methodology and Statistical Tools

The generally applied method in attempting to fulfil the research objective was that of Structural Equation Modelling in combination with quantitative survey research. In this chapter, the SEM methodology as well as its suitability in this project will be explained. Further, the tools involved to perform the analysis are presented. The chapter then proceeds by explaining the relevant indicators from the SEM analysis' output which will be used in the presentation and evaluation of the results.

4.1.1 Structural Equation Modelling

Here the SEM methodology is discussed through its background, concept, advantages and key features from chapter 4.1.1.1- 4.1.1.3. The chapter then proceeds by describing the reasoning behind choosing SEM to perform the analysis in chapter 4.1.1.4.

4.1.1.1 Background and Concept

Structural Equation Modelling (SEM) is a form of causal modelling which makes use of multivariate statistical analysis techniques to analyse structural relationships. The roots of the modelling technique stretch back to 1921 from Sewall Wright's work on path analysis and have been later modified and extended to what it is today (Wright, 1934). The technique combines factor analysis and multiple regression to analyse the relationships between measured variables and latent variables. In this context, a latent variable is a variable that cannot be directly measured in the same way as for instance height, age or years studied. The measurement procedure of the latent variables, therefore, involves an alternative technique. This technique concerns combining a set of measurable items that relates to the latent variable in order to achieve measurement.

SEM is a particularly popular methodology in quantitative social and behavioural science because it often concerns researching phenomena which cannot be directly observed. As we can only make inferences about what is observed, SEM's ability to measure unobservable variables functions as a solution to this issue. A classic example is the measurement of intelligence. This cannot be directly measured as it consists of several elements such as the mathematical, spatial, verbal and logical ability. However, as these items can be measured individually, a combination can be used to measure intelligence as a latent variable (Kline, 2015).

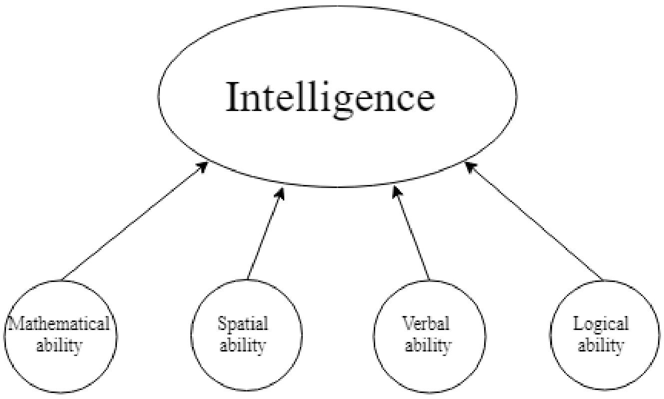

Figure 5. Example of a latent variable

4.1.1.2 SEM and Complex Models

A rare feature which is embedded in SEM is the ability to analyse models where variables function as both independent and dependent simultaneously. This allows researchers to build and analyse complex models where a large number of variables are believed to be interdependent. Additionally, the methodology can distinguish between direct, indirect and total effects among variables. These two features combined plays an important role in giving researchers flexibility when designing causal models (Kline, 2015; Ullman, 2006).

4.1.1.3 Measurement Error in SEM

Another special feature in SEM is the effect that latent variables have on the measurement error. If the measured items were to be analysed individually, a significant measurement error caused by multiple factors would strongly affect the results' accuracy. By combining the items, the summed error variance represents a latent variable. Hence, in this variable, all the variance the items share is represented, and the items' measurement error is not present. Instead, all the variance the measured items do not share is considered the latent variables' measurement error (Kline, 2015).

Given that the items make suiting measures (further discussed in chapter 5.1.3), this measurement error is considerably lower than if the individual items were analysed in the model. Hence, SEM can lead to lower measurement error than traditional methods such as regression analysis.

4.1.1.4 Choosing SEM to Perform The Analysis

The conceptual framework in chapter 3.4 involves a set of variables which almost exclusively cannot be directly measured. For instance, the analysis' key variable of knowledge and familiarity with BEVs among consumers, consists of several factors (performance, usage, running costs etc.) and cannot be directly determined. In other words, a method capable of dealing with this issue must be applied. By choosing SEM, we can combine several measurable items related to the framework's variables and develop measurable latent variables as discussed in 4.1.1.1.

Further, as our conceptual model has a high level of complexity through 8 variables and a total of 16 hypothesised effects, it's essential to choose a method which can deal with this complexity. In addition, SEM is capable of analysing the model's multiple variables which functions as both dependent and independent variables simultaneously (e.g. perceived risks, perceived usefulness and attitude).

When considering these key features, SEM appears as a suiting alternative to analyse our causal model. It should also be mention that there exists other techniques which could be applied to analyse models of this complexity. However, due to accessibility to expertise on SEM in the author's local environment (e.g. faculty staff), it appeared as a natural choice of methodology when analysing the conceptual model.

4.1.2 Model Fit (Confirmatory Factor Analysis)

SEMs can come in many forms and be highly varying in complexity level through the number of measured variables, latent variables and relationships between variables. However, they share the same evaluation process when analysing the models. More precisely, in order to be considered a well-fitting model and hence supporting a researchers hypothesis, a structural model must fulfil a set of criteria.

In this process of evaluating the model, a confirmatory factor analysis (CFA) is conducted to test the reliability and validity of the analysed model. CFA is a form of factor analysis developed by K.G. Jorenskog in 1969 that involves several steps in which a researcher must test a model's measurements and model fit in line with a hypothesis (Jöreskog, 1969). After the publication in 1969, the CFA has been further developed and still functions as a highly relevant method of factor analysis to this day. The various model fit indicators are described below, while the corresponding values from our analysis are presented in the results chapter.

Absolute fit indices.

- *Chi-squared test:* Indicates the magnitude of covariance between the observed and expected covariance matrix. The lower the value, the better the model fit as it indicates a small difference between the covariance matrixes. The acceptable values vary to some degree among researchers, but a common rule is $\chi^2/df < 2$ and $p>.05$. A notable weakness of this measure is that it can favour small sample sizes and disfavour large sample sizes.
- *Root mean square error of approximation (RMSEA):* This method analyses the inconsistency between the hypothesized structural model with optimal parameter estimates and the population covariance matrix and thus avoids the issues related to sample size. The values range from 0 to 1 where a lower value indicates a better fit. Generally values lower than .06 are considered acceptable.
- *Standardized root mean square residual (SRMR):* Refers to the square root of the difference between residuals (observed value of the dependent variable minus predicted value) of the sample and hypothesised covariance matrixes. Lower values than .08 are considered acceptable levels.
- *Goodness of fit statistic (GFI):* Calculates which proportion of variance that can be accounted for by the estimated population covariance. The strength of this indicator is that we can see how closely the predicted model is to replicate the observed covariance matrix. Different values have been considered acceptable, but most make use of values above .90 or .95.

(Hooper, Coughlan, & R. Mullen, 2007)

Relative fit indices.

- *Normed-fit index (NFI):* Compares the Chi-square of the model to the null model, where the null model is a worst case scenario where all the measured variables are uncorrelated (similar to a null hypothesis). The output values range from 0 to 1 where values above .95 generally are considered acceptable for a good fitting model. An issue of this model is that it underestimates fits for small sample sizes.
- *Comparative fit index (CFI):* As with NFI this index assumes the latent variables are completely uncorrelated, but compares this to the sample covariance matrix and is thus is effective regardless of smaller sample sizes. Just as with the NFI, the acceptable values are usually considered to be above .95.

(Hooper et al., 2007)

4.1.3 Applied Tools: IBM SPSS and AMOS

There are several statistical tools available to perform the necessary analysis in this study. The choice fell on IBMs SPSS for the general statistical analysis, while the IBM's SEM software AMOS was used to analyse the structural models. The choice was primarily based on accessibility as SPSS is a part of TUDelft's available software to its students. While AMOS, which is produced by the same company as SPSS, was chosen as it allows for flawless interaction between the programs.

4.2 Measures

There are different approaches to performing the structural equation modelling (SEM) in line with the research objective. The common and chosen approach was an extensive questionnaire study as it fits the nature of the research. When conducting this approach, a questionnaire is designed with the purpose of containing items which combined can explain the latent variables in the structural model. The common practice is to construct 3 or more items for each latent variable, while lower quantities also can be deployed. In this chapter, the development of the survey design as well as the items is presented.

4.2.1 Survey Design

4.2.1.1 Part 1: Communicated Information and Demographic Profile

The questionnaire consists of two parts. The first consist of information about the questionnaire as well as the demographic profile of the participant.

4.2.1.1.1 Information

The information presented to respondents reads as follows:

"For the final project of my master program at TUDelft, I am doing research on the opinion of electric cars in Norway and the factors influencing investments in the vehicles. Therefore, I am greatly interested in the input from Norwegian citizens with a wide range of demographics to create a generalizable picture. The survey should only take 3-5 minutes and your response is completely anonymous. Thank you for answering my survey, your input is much appreciated!"

The inclusion of this information serves a set of purposes:

- Informing participants that all answers are completely anonymous, which ideally removes the bias related to reporting desired behaviour (common method bias).
- Explaining why the researcher is interested in the demographic profile.
- It aims to properly thank participants for taking the time to respond as well as explaining why their input is valuable.

4.2.1.1.2 Demographic Profile

The demographic profile to be filled in by participants was restricted to involve:

- Gender
- Age
- Educational level
- Current car ownership status

Although these measured items are not a part of the variables in the framework, they are included in order to determine the generalizability of the results. It is also included in order to detect potential biases. Particularly the inclusion of the participants' car ownership status is important to determine the generalizability of the results as it might influence the responses. In addition, the demographics allow for a sub-analysis where adoption intention of BEVs can be characterised based on demographics.

4.2.1.2 Part 2: Measurable Items

The second part of the questionnaire consist of the items making up the latent variables.

4.2.1.2.1 Measurement Scale

The items were measured on a seven-point Likert scale where respondents are asked to indicate how much they agree with a statement. The numerical values were further described to be correspond to the following level of agreeability.

1= Strongly disagree
2= Disagree
3= Mildly disagree
4= Neutral
5= Mildly agree
6= Agree
7= Strongly agree

The Likert scale was implemented as it results in practical data to analyse through the analysing tools of SPSS and AMOS. Further, the seven-point scale was preferred over the more common five-point scale as it allows for more accurate indications for participants.

4.2.1.2.2 Items Making up the Latent Variables

Part of the measured items are based on the works of Shanyong Wang et al. in the inspirational study, which again is based on previous research in relation to their respective latent variables (Wang et al., 2018). The changes and additions to the works in the inspiration study were primarily a result of the pilot survey issued during the work of this project. Other changes occurred as the framing of the questions were perceived to lack candidness. This issue related to framing could be explained by translation complications or cultural differences. In addition, items were developed for the variables deviating from the Chinese study. The results of this process are hereby presented in groups relating to the variable each item measures.

Knowledge of BEVs (KB)

KB1: I am familiar with the performance of electric cars (e.g., charging time, acceleration, driving comfort and driving range).
KB2: I am familiar with the general expenses of using electric cars (e.g., charging costs).
KB3: I know about the advantages of electric cars over gasoline and diesel cars.

Perceived Risks (PR)

PR1: I am afraid of financial losses when using electric cars (e.g., Battery replacement, maintenance costs).
PR2: I would not feel totally safe when I drive an electric car on the road.
PR3: Considering the disadvantages of electric cars (e.g., limited driving range and long recharging time), I think they involve important time losses.
PR4: I worry about becoming less flexible/mobile if I buy an electric car (travel distance and recharge time).

Perceived Usefulness (PU)

PU1: Electric cars are useful to reduce carbon emissions.
PU2: Electric cars are useful to reduce my spending on transportation.
PU3: Electric cars are useful to improve air quality.

Attitude BEVs (AB)

AB1: I am interested in electric cars.
AB2: For me, buying an electric car is a good decision.
AB3: I think electric cars generally should replace gasoline and diesel cars.

Intention to Adopt (IA)

IA1: I am willing to buy an electric car when buying a car in the future.

IA2: I plan to buy an electric car when buying a car in the future.

IA3: An electric car is the best option for me when buying my next car.

Incentive Policies (IP)

IP1: I think the policy for electric cars is good enough. (If you are not familiar, do not answer)

IP2: I think the charging infrastructure for electric cars in Norway is good enough. (If you are not familiar, do not answer)

Awareness of Incentives (AI)

AI1: I know well about the Norwegian electric car policy (subsides, toll, parking, tax exemptions etc.) for electric cars.

AI2: I know well about the charging infrastructure for electric cars in Norway.

Comparison to ICEVs (CI)

CI1: I think electric cars offers better performance for the price than gasoline or diesel cars (performance= driving comfort, acceleration etc.).

CI2: I think electric cars involves lower overall risks than gasoline or diesel cars (risk= safety, financial etc.).

CI3: I think electric cars offer better value for the price than gasoline or diesel vehicles (value= running costs, performance, design, risk etc.).

4.2.2 Pilot Survey

As stated in chapter 6.1, a pilot survey was executed as a part of developing the finetuned measurable items presented above. The Pilot involved approximately 30 responses as well as consultation with relevant academics and communication with a set of respondents. This led to multiple adjustments as previously addressed in this chapter. However, the primary purpose of the pilot was to determine the reliability of the measured items in relation to the corresponding latent variable. This details of this procedure, as well as the results from this analysis, are presented in chapter 7.

4.2.3 Target Population and Data Collection

The goal of the collection procedure was to compose a sample which was representative for the typical Norwegian consumer above the age of 18. No part of the population were to be excluded, not even those currently not holding a driver’s license as they might do so in the future. To keep track of the participating sample, the demographic profile described previously in the chapter was introduced. The results of these profiles are presented in chapter 5.1.1.

The data was collected by a combination of convenience and snowball sampling where an online survey was spread through social media. Due to free accessibility and intuitive user interference, Google’s survey tool “Google Forms” was utilized to collect the data. The survey was first presented to approximately two dozen people in the researcher's network (convenience) across the country, and then spread through Facebook publications and sharing from the selected respondents (snowball). Though sharing occurred in different parts of the country, the South, West and East part of Norway were more represented than the North. Further, we’d like to point out that the participation was not rewarded by remuneration of any kind. The biases related to this data collection procedure will be discussed when evaluating the findings later on in the report.

5 Results

In this chapter, the results from analysing the structural model aiming to determine the validity of the conceptual model from the research framework are presented. Further, the results of a regression analysis between the demographic profile and the intention to adopt a BEV is included. Lastly, due to an issue which occurred through the reliability analysis explained in 5.1.4, an additional regression analysis on governmental involvement is presented.

5.1 The Structural Model (Knowledge Analysis)

5.1.1 Demographic Profile of The Collected Sample

The data collection resulted in 311 respondents resident in various parts of Norway with widely spread age and educational levels as shown in table 1. In addition, the questionnaire asked the participants to fill in their current vehicle ownership status which revealed that approximately half of the 311 participants owned a BEV. This can be explained by an interest in participating in research concerning a familiar topic. In order to analyse a more representative sample, the responses were therefore reduced by excluding the most recent participants which had owned a BEV in addition to statistical outliers while maintaining a recommended sample size. This resulted in a sample of 266 participants with the demographics showed in table 1. As the table shows, the sample can mostly be considered to achieve the goal described in chapter 4.2.3 of representing the typical Norwegian consumer above 18 years old. However, the ownership status should be considered as a potential bias when evaluating the results as there is an overweight of BEV users compared to the actual population (Statistisk Sentralbyra, 2019).

Table 1. Demographic profile of participants

Demographic variable (N=266)	Frequency	Percentage [%]
Gender		
Female	85	32
Male	181	68
Age group		
18-25	9	3
26-35	23	9
36-45	73	27
45-55	116	44
Above 55	45	17
Educational level		
High school or below	91	34
Bachelor’s degree	87	33
Master’s degree or above	88	33
Car ownership status		
BEV	145	54
ICEV	87	33
Hybrid	18	7
Future owner	10	4
Non future owner	6	2

5.1.2 Common Method Bias

Before addressing the reliability of the latent variables in the model, the items measured in the questionnaire were tested for common method biases through Harmon's one-factor test. The test is executed to evaluate whether the responses in the survey are caused by the instrument rather than the actual predispositions of the survey respondents (Izenman, H. Harman, G. Joreskog, E. Klovan, & Reyment, 1978). This is particularly important to address in research of this nature, as respondents might feel pressure to communicate desirable behaviour such as appearing positive towards environmentally friendly solutions.

To perform the test, all measured items are included in a single factor analysis and tested for "total explained variance". According to Harmon, the single factor should account for less than 50% of the total variance in order to not be subject to significant common method bias. (Izenman et al., 1978)

The test was performed in SPSS and resulted in a total of 43.6% of the total variance, which indicates that common method bias should not be a problem when performing the analysis (See appendix A). The research could therefore proceed. The measure of informing the respondents that their responses were completely anonymous could have been useful to achieve this, as well as striving to frame the questionnaire as neutral as possible.

5.1.3 Scale Reliability Test

As a first step to analysing the structural model, the measured variables (e.g. questions from the survey) making up the model's latent variables were evaluated through a scale reliability analysis. This is performed in SEM to make sure that the measured variables are good indicators and makes a reliable measure of the latent variables. The analysis is divided into three steps.

First, the Cronbach's alpha (α) values are calculated through the built-in reliability measurement tool in SPSSs. In this context, the α can be seen as the internal consistency of a latent variable which determines how closely the measured items are as a group. Levels above .7 are generally considered acceptable, while increasingly higher values indicate higher scale reliability (Iacobucci & Duhachek, 2003).

Secondly, the latent variables were evaluated in terms of Composite reliability (CR) which similarly to the previous measure of α concerns the internal consistency. The method is considered by some researchers to be a more accurate estimate than Cronbach's Alpha as the α calculation makes assumptions which can lead to lower bound and underestimating the true reliability (Peterson & Kim, 2013). Further, the CR has similar acceptance values as the Cronbach's Alpha and was calculated with the formula presented beneath. In the formula, the λ refers to the individual factor loadings of each measured item which was found through testing the effect of the item on the latent variable in AMOS.

$$CR = \frac{(\sum_{i=1}^{n} \lambda)^2}{\left(\sum_{i=1}^{n} \lambda_i\right)^2 + \sum_{i=1}^{n}(1 - \lambda_i^2)}$$

Lastly, the Average Variance Extracted (AVE) was calculated for the latent variables. This is a test which measures the variance captured by a latent variable in comparison to the measurement error. The generally considered acceptable values are .5 and above, and the indicator is calculated with the following formula (Hair, Black, Babin, Anderson, & Tatham, 2006):

$$AVE = \frac{\sum_{i=1}^{n} \lambda_i^2}{\mathrm{n}}$$

5.1.4 Results of Scale Reliability Test

The scale reliability analysis revealed that two of the latent variables in the original hypothesised framework could not be considered good indicators for what they were aimed to measure. The two variables were the strictly independent variables of Incentive Awareness (IA) and Incentive Policy (IP). In addition to poor performance in the reliability analysis, the scales were not ideal to be included as they consist of two items (Eisinga, Grotenhuis, & Pelzer, 2013).

In retrospective, these latent variables could have been constructed differently although they passed the control organ of the pilot survey. The two variables were therefore disregarded from the SEM analysis and attempted evaluated through a separate analysis presented in chapter 5.2. A potential explanation could be that the variables did not experience internal consistency as they concerned two different aspects of government involvement, namely charging networks and incentives.

Apart from this issue, the rest of the seven latent variables fulfilled all required criteria to make reliable measures. The results of this analysis are presented in the following table, as well as in appendix C.

Table 2. Scale reliability results

Constructs and Indicators (N=266)	Loading	CR	AVE
Knowledge BEV (KB)			
KB1: I am familiar with the performance of electric cars (e.g., charging time, acceleration, driving comfort and driving range).	0.87		
KB2: I am familiar with the general expenses of using electric cars (e.g., charging costs).	0.93		
KB3: I know about the advantages of electric cars over gasoline and diesel cars.	0.78		
Reliability of summated scale.	α = 0.90	0.90	0.75
Perceived Risk (PR)			
PR1: I am afraid of financial losses when using electric cars (e.g., Battery replacement, maintenance costs).	0.59		
PR2: I would not feel totally safe when I drive an electric car on the road.	0.64		
PR3: Considering the disadvantages of electric cars (e.g., limited driving range and long recharging time), I think they involve important time losses.	0.78		
PR4: I worry about becoming less flexible/mobile if I buy an electric car (travel distance and recharge time).	0.86		
Reliability of summated scale.	α = 0.80	0.81	0.53
Perceived Usefulness (PU)			
PU1: Electric cars are useful to reduce carbon emissions.	0.76		
PU2 Electric cars are useful to reduce my spending on transportation..	0.55		
PU3: Electric cars are useful to improve air quality.	0.78		
Reliability of summated scale.	α = 0.73	0.74	0.50
Attitude BEV (AB)			
AB1: I am interested in electric cars.	0.81		
AB2: For me, buying an electric car is a good decision.	0.97		
AB3: I think electric cars generally should replace gasoline and diesel cars.	0.73		
Reliability of summated scale.	α = 0.87	0.88	0.71
Intention to Adopt (IA)			
IA1: I am willing to buy an electric car when buying a car in the future.	0.93		
IA2: I plan to buy an electric car when buying a car in the future.	0.95		
IA3: An electric car is the best option for me when buying my next car.	0.91		
Reliability of summated scale.	α = 0.95	0.95	0.87
Comparison to ICEV (CI)			
CI1: I think electric cars offers better performance for the price than gasoline or diesel cars (Performance= driving comfort, acceleration etc.).	0.81		
CI2: I think electric cars involves lower overall risks than gasoline or diesel cars (Risk= safety, financial etc.).	0.75		
CI3: I think electric cars offer better value for the price than gasoline or diesel vehicles (Value= running costs, performance, design, risk etc.).	0.88		
Reliability of summated scale	α = 0.85	0.86	0.67

5.1.5 The Analysed Structural Equation Model

As discussed in chapter 5.1.4, the measurements of the influence of the governmental involvement proposed through the hypothesised model (IA and IP) failed the reliability analysis. Though this was not desirable, the variables were both exclusively independent variables and were only hypnotised to influence the Intention to Adopt (IA). The means that the rest of the model still could be analysed with the key purpose of understanding consumers BEV Knowledge and the influence on the Adoption Intention and Comparison to ICEVs.

After performing the scale reliability analysis, the structural model was adjusted to exclusively include the latent variables which fulfilled the requirements for measurement reliability. The model can be seen in figure x including the hypothesised effects among the variables. The smaller circles represent each of the measured items (e.g. questions in the survey), while the large ovals refer to the following latent variables.

- Knowledge of BEVs (KB)
- Perceived risks related to BEVs (PR)
- The perceived overall usefulness of BEVs (PU)
- The general attitude towards BEVS(AB)
- Intention to adopt/buy a BEV (IA)
- The opinion of the comparison between BEVs and ICEVs (CI)

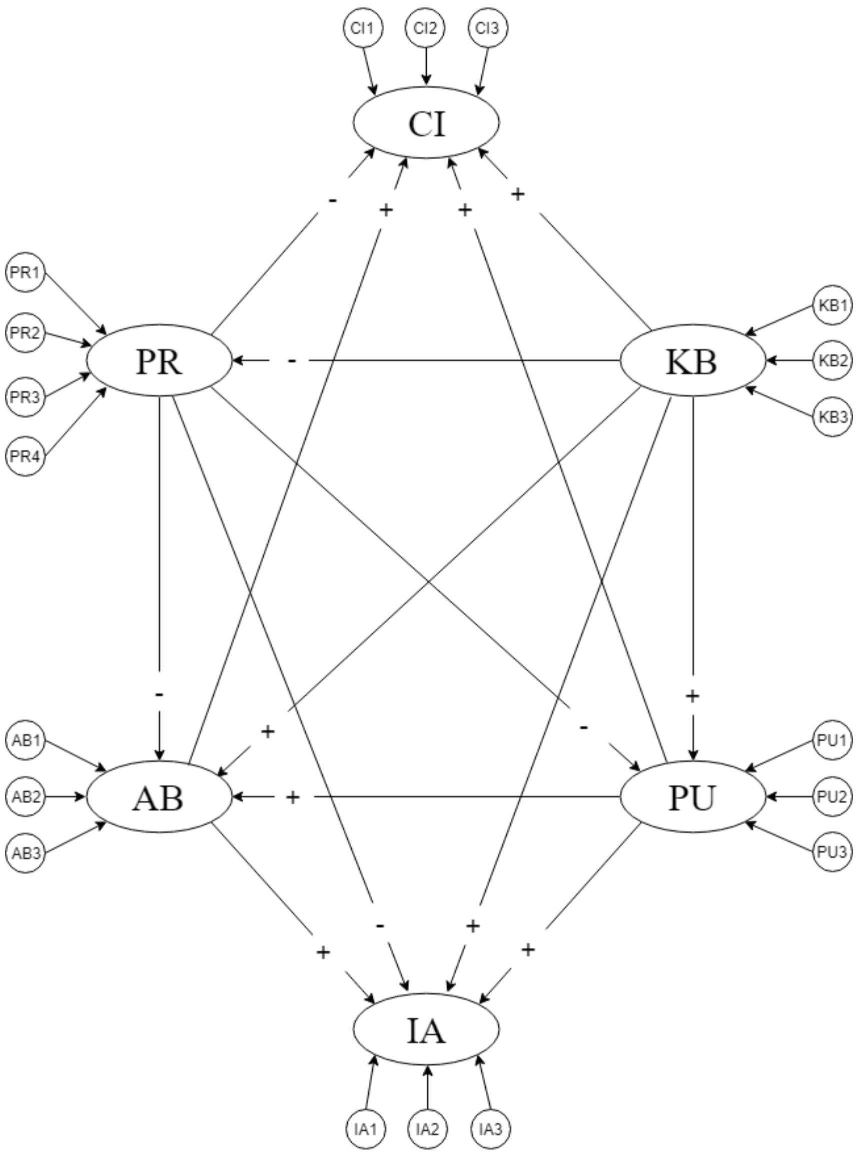

Figure 6. The analysed structural model

5.1.6 Input in AMOS Analysis

When performing the analysis in AMOS, a technique known as "summated scales" which is common in complex structural models was utilized. This technique is used because performing the analysis directly with all 21 items and 7 latent variables would require all error terms to be uncorrelation to indicate a good model fit. When summating the items in each latent variable, the number of error terms are reduced, and we can analyse the model with an emphasis on the latent variables without the distraction from correlated error terms (Blunch, 2015).

To perform the summated scale technique, each group of indicating items, for instance, KB1, KB2 and KB3, were summated into a single variable in SPSS. This new variable then replaces the items it represents when performing the analysis in AMOS. Further, the error term of the summated variable is calculated based on the scale variance and Cronbach's Alpha of each latent variable found in the previously mention reliability analysis in SPSS. The error variance was then calculated with the following formula and fixed in the updated AMOS model (Blunch, 2015).

$$Error\ variance = \text{Scale variance} * (1 - \alpha)$$

This equation also demonstrates the importance of having high scale reliability as it decreases the error variance of the variable. After this procedure, the structural model was ready to undergo the analysis in AMOS to investigate whether the conceptualized model functioned as a well-fitting model. The findings are presented in the next chapter.

5.1.7 Confirmatory Factor Analysis

The model fit evaluation was performed through the Confirmatory Factor Analysis (CFA) elaborated in chapter 4.1.2. In short, the analysis of the structural model gave very positive results. The AMOS software indicated that the data matched the hypothesis, but some of the directional effects were redundant as the effects occurred through mediation rather than direct effects. For instance, the analysis suggested that knowledge does not directly affect the Intention to buy an EV, but it does so through reducing the perceived risks, increasing the perceived usefulness and improving the attitude towards the vehicles.

After the adjustment of removing redundant directional arrows, the "model fit indices" tool in AMOS indicated that the model was a good fit with the following results. For a description of each indicator, see chapter 4.1.2. The original output of this analysis in AMOS is also presented in appendix I.

Table 3. Confirmatory factor analysis results

Model fit indicator	Acceptable value	Measured value	Results
χ2/df	χ2/df <2.0 and p>.05	.53 and .72	Approved
RMSEA	<.06	0	Approved
SRMR	<.08	.005	Approved
GFI	>.95	.99	Approved
NFI	>.95	.99	Approved
CFI	>.95	1	Approved

As the table shows, all the measured values in relation to the CFA fulfilled the criteria discussed in chapter 4.1.2. This indicates that we have a good-fitting model. In this context, a good fit refers to the model's ability to reproduce data and suggests that it is reasonably consistent and does not necessarily require re-specification. It should be noted that this not necessarily mean that we have a valid model, but it is necessary to achieve a good fit before interpreting the casual paths which will be discussed from chapter 5.1.8.

5.1.8 The Estimated Model

5.1.8.1 Descriptive Statistics

In the table, each latent variable's internal mean and standard deviation is calculated. Lastly, the correlations between the latent variables are presented with a p-value lower than .01. (See appendix B)

Table 4. Descriptive statistics for structural model

Latent variable	Mean	SD	KB	PR	PU	AB	IA	CI
KB- Knowledge BEV	5.82	1.32		-.56	.48	.62	.61	.57
PR- Perceived Risks	3.15	1.41	-.56		-.51	-.67	-.69	-.67
PU- Perceived Usefulness	5.37	1.27	.48	-.51		.67	.60	.66
AB- Attitude BEV	5.29	1.61	.62	-.67	.67		.90	.77
IA- Intention to Adopt	5.74	1.61	.61	-.69	.60	.90		.76
CI- Comparison to ICEV	4.96	1.38	.57	-.67	.66	.77	.76	

Note: All estimates are significant at p<0.01

The descriptive statistics revealed that the mean values of both "Knowledge BEV" and "Intention to Adopt" were very high among the sample with respectively 5.82 and 5.74 on the 7-point Likert scale. Other interesting results was the high evaluation of the comparison to ICEVs as well as the relatively low perceived risks.

5.1.8.2 Magnitude of Effects

The AMOS analysis further calculated the following standardized total effects among the latent variables in the model in the model. (Appendix F and G)

Table 5. Standardized total effects for structural model

DV / IV	PR	PU	AB	IA	CI
KB	-.67	.61	.69	.66	.65
PR		-.48	-.62	-.63	-.67
PU			.52	.32	.53
AB				1.27	.40

Note: All estimates are significant at p<0.01

The analysis indicates that Knowledge had strong standardized total effects with coefficients over .6 on usefulness, attitude, intention to adopt as well as the comparison to ICEVs. Here, the standardized coefficient refers to how many standard deviations the dependent variable follows a change of one standard deviation in the independent variable (Knowledge in this case) when variance is set to 1. Further, knowledge had a strong and negative standardized effect on the perceived risks. Other notable findings is the magnitude of the risk perception on "intention to adopt" which reached a negative value of .67, as well as the very impactful attitude variable which showed the strongest standardized total effect of 1.27.

5.1.8.3 Hypothesis Testing

The results are presented in the form of hypothesis testing in table 6. If there exists an effect with p-values lower than .05 the hypothesis is supported.

Table 6. Hypothesis testing in structural model

Hypothesis	**Path coefficient (std)**	**P-value**	**Result**
KB → IA (+)	.66	<0.01	Supported
KB → PU (+)	.61	<0.01	Supported
KB → AB (+)	.69	<0.01	Supported
KB → PR (-)	-.67	<0.01	Supported
KB → CI (+)	.65	<0.01	Supported
PR → PU (-)	-.48	<0.01	Supported
PR → AB (-)	-.62	<0.01	Supported
PR → IA (-)	-.63	<0.01	Supported
PR → CI (-)	-.67	<0.01	Supported
PU → IA (+)	.32	<0.01	Supported
PU → AB (+)	.52	<0.01	Supported
PU → CI (+)	.52	<0.01	Supported
AB → IA (+)	1.27	<0.01	Supported
AB → CI (+)	.40	<0.01	Supported

The presented data supports all the developed hypothesises' in chapter 3.3 and 3.4. Further, all estimations fulfilled the significance requirements with p-values lower that .01.

5.1.8.4 Illustration of Estimated Model Including Effects

The following figure illustrates the standardized total effects in the form of a path diagram. The stapled lines refer to the abovementioned relationships which strictly consists of mediation

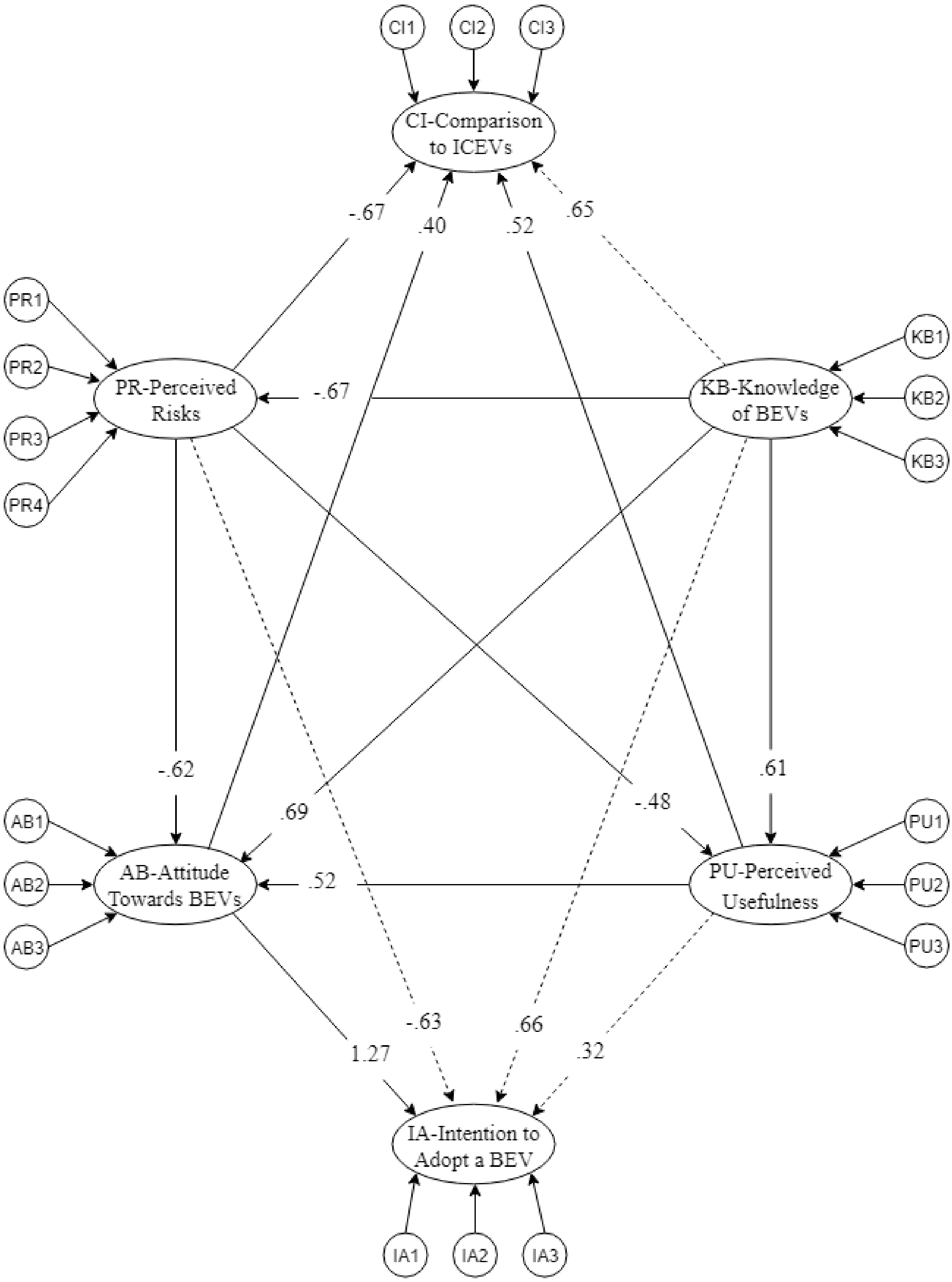

Figure 7. Illustration of the standardized total effects in form a structural model.

5.2 Regression Analysis (Incentive and Charging Network)

As discussed previously in the chapter, the reliability analysis revealed that the items making up the latent variables Awareness of Incentives (AI) and Incentive Policy (IP) could not be used in the structural equation model. It is possible that this was caused by grouping incentive policies with charging networks, though other explanations could exist as well. However, in an attempt to make use of the collected data to reach the research objectives, a separate analysis took place.

The analysis involves a basic linear regression model where the intention to adopt (IA) were regressed on the independent variables in our hypotheses. More specifically this included the four items making up the IA and IP variables as well as the measured BEV knowledge (KB). Through this analysis, the relationship between adoption intention and the AI, IP and KB variables can be determined and compared (Laerd Statistics, 2018).

5.2.1 Dealing with Missing Data

Through the survey design in chapter 4, respondents were given the option to not respond to two of the items, namely IP1 and IP2, which measured the satisfaction with the Norwegian incentive policy and charging network. This option was provided in order to avoid that respondents reported satisfactory levels on something they had little knowledge or familiarity with as it would have caused a bias in the measure. In total this led to 12% (IP1) and 9% (IP2) missing data on the items.

There are many ways of dealing with missing data in quantitative research of this nature, but in cases where the causes are non-random (NMAR), the solutions are complex and can potentially introduce additional bias if performed inaccurately. For instance, the approach of Multiple Imputation, which runs simulations on missing data relative to the data that is available in order to replace the missing data, could have functioned as such a solution (Manly & Wells, 2015).

However, as the missing data was controlled, relatively low and the cause logically explained, it was decided to perform the analysis by excluding the responses with the missing data. This approach in combination with reflecting on the potential bias was preferred over performing an analysis with a number of pitfalls. Further, it could be problematic to assign values to an item which would indicate an opinion that in reality did not exist among the respondents.

5.2.2 Descriptive Statistics

After excluding the responses with missing data, the sample size was reduced to 213, while the sample's demographic profile did not significantly change from that of table 1. The descriptive statistics of the analysis from SPSS regression function are presented in the following table as well as in appendix E.

Table 7. Descriptive statistics of incentive analysis

Variable	Mean	SD	KB	AI1	AI2	IP1	IP2	IA
KB- Knowledge BEV	6.04	1.13		.32	.31	.44		.56
AI1- Awareness Incentives	6.29	.99	.32		.53	.40	.16	.32
AI2- Awareness Incentives	5.47	1.30	.56	.53		.35	.34	.31
IP1- Incentive Policy	5.29	1.62	.50	.40	.35		.23	.44
IP2- Incentive Policy	3.62	1.50		.16	.34	.23		
IA- Intention to Adopt	5.91	1.57	.56	.32	.31	.44		

Note: All presented estimates are significant at p<0.01

Among the most notable descriptive statistics was that the mean of the incentive awareness variable was as high as 6.29 on the 7-point Likert scale. This indicates that the Norwegian government has been very successful in spreading information regarding their incentive policy. Another finding worth mentioning is the low satisfactory levels with the charging infrastructure (3.62 on the 7-point Likert scale). This is interesting considering the high levels of intentions to adopt BEVs despite the dissatisfaction. On the other hand, the statistic corresponds well with the mentioned pressured Norwegian charging networks discussed in chapter 1.

5.2.3 Results of Regression Analysis

The results of the regression analysis indicated that awareness of both incentives and charging networks had a weak, yet significant positive effect on adoption intention. Further, the satisfaction levels with the incentive policy had a stronger positive effect than that of awareness. Lastly, the satisfactory levels with charging infrastructure had no significant relationship. It should be noted, however, that all these effects were significantly lower than that of knowledge on intention to adopt. The results are presented in the following table as well as appendix E.

Table 8. Results of analysis of adoption intention regressed on the items making up AI, IP, KB.

Item	R Square Adjusted	Standardized Beta	T-value	P-value	Results 95% confidence
KB AVG	.30	.55	9.52	<0.01	Approved
AI1	.08	.30	4.51	<0.01	Approved
AI2	.09	.31	4.65	<0.01	Approved
IP1	.17	.42	6.62	<0.01	Approved
IP2	.01			>0.05	Rejected

Note: For a description of the questions making up the items, see table x

5.3 Demographic Analysis

Although demographic predictions were not a part of the original hypothesis, all the data for performing such an analysis was provided in the survey design. As the overall goal of the study was to add to the understanding of BEV adoption, an analysis was performed to identify patterns in relation to gender, age and education. More specifically, the predictive analysis of linear regression was used to perform the evaluation. This was performed directly through SPSS' regression tool (Statistics Solutions, 2013).

5.3.1 Decoding Variables

The items making up the demographics were not measured on a numerical rating scale as the rest the measured items. Therefore, the responses had to be decoded in order to perform the regression analysis. This was done in the following way for each of the variables.

- *Gender*: In the survey, respondents were given the options of female or male. The values were therefore changed to binary indicators of 0 for female and 1 for male. The results were then analysed in regard to standard values due to the different scales among the independent and dependent variable.
- *Educational level*: The Norwegian educational system following high school is fairly straight forward where you go into ''higher education' levels of firstly a bachelor degree (3years) then a Masters (2 additional years), followed by a potential PhD. In the survey, respondents were given the following options: VGS (High school), Bachelor or Master (or higher). In the decoding process, these were translated to the number of higher education studied. In other words, VGS translated to 0, Bachelor to 3 and Master to 5.

- *Age*: The survey design made use of age groups of 10 years in each group. These were simply translated to numerical values where the lower group was assigned a 1, and the rest in increasing order. Although the first (18-25) and last (above 55) categories did not consist of intervals of 10 like the other categories, their low quantities meant that it would not significantly change the outcome by addressing this minor issue. 18-25 was therefore assigned a 1, while above 55 was assigned a 5.

5.3.2 Descriptive Statistics

In the table, each variable's internal mean and standard deviation is calculated. Lastly, the correlations between the latent variables are presented with a p-value lower than .01. The direct output from the SPSS analysis can be found in appendix D.

Table 9. Means, standard deviations and correlations

Variable	Mean	SD	Correlation to adoption intention
Adoption intention	5.74	1.64	
Gender (nominal)	.68 (68% male)	.47	.23
Age	3.62 (≈45 years)	.98	
Higher education	2.64 years	2.07	.20
Note: In the gender analysis, positive values indicate that men have higher intentions to adopt			

The statistics showed that there was an overweight of men participating in the survey, that the average age was approximately 45 years, and that the sample was relatively highly educated with an average of 2.64 years of higher education.

5.3.3 Results of Regression Analysis (Demographic Profile)

The regression analysis showed that gender and education had a weak, yet significant effect on adoption intention of BEVs. Further, Age was revealed to have no significant effect among the sample population. The results are presented in the table beneath as well as in appendix D.

Table 10. Results of analysis of adoption intention regressed on the items making up the demographic profile.

Item	R Square Adjusted	Standardized Beta	T-value	P-value	Results 95% confidence
Gender	.06	.23	3.95	<0.01	Approved
Age	.00			>0.05	Rejected
Education	.04	.20	3.43	<0.01	Approved
Note: In the gender analysis, positive values indicate that men have higher intentions to adopt					

6 Discussion, Conclusion and Managerial Implications

6.1 Discussion

6.1.1 Exploring the Results

The main purpose of this thesis was to develop a deeper understanding of how knowledge affects consumer's intentions to adopt BEVs as well as the side-by-side comparison with ICEVs. The study also attempted to compare these effects to that of governmental incentives and charging networks as well as evaluating perceived risk as a barrier against diffusion. On a more detailed level, the study aimed to do so through a structural model based on an extended technology acceptance model (TAM). This structural model involved the original TAM variables of perceived usefulness and attitude, as well as the additional variables of perceived risks, governmental incentives, charging networks, adoption intention, comparison and knowledge. Further, this structural model was analysed through structural equation modelling to validate the hypothesis presented. However, due to complications in the reliability analysis of the measured items, a separate analysis was set up for the model's strictly independent variables of incentive policies and charging networks.

The results of analysing the structural model indicated that the hypothesised model was indeed a good fit by fulfilling all the standard model fit indicators in the confirmatory factor analysis. This means that the tested model (and its hypothesis) fits the collected data and that the model could correspond to reality as the null hypothesis is rejected. Moreover, the results suggested that knowledge had a strong and significant effect on both the intention to adopt BEVs ($\beta = .66$) as well as the direct comparison ($\beta = .65$) through mediating effects of perceived usefulness, risk reduction and improved attitude towards BEVs. Further, as predicted, the perceived risks related to BEVs functioned as a strong barrier against the intention to adopt ($\beta = -.63$) through reducing the perceived usefulness and negatively effecting consumers attitude towards BEVs. In short, all the proposed hypothesises in the analysed structural model was supported by the structural equation modelling procedure.

Further, the results supported the predictions among the variables in Davis' TAM by a positive effect from perceived usefulness on the attitude towards BEVs ($\beta = .52$) and adoption intention ($\beta = .32$). Further, in line with Davis's TAM, the attitude had a strong and positive effect on adoption intention ($\beta = 1.27$) (Davis et al., 1989). This corresponds well to the previous research discussed in chapter two, which found the attitude to be among the strongest influencing factors on consumers when considered green alternatives (Ha, 2012; Söderlund, 2002; Zografakis et al., 2010).

Moreover, a high degree of BEV knowledge was suggested as a driver for the disproportionally high adoption rates in Norway compared to other proactive countries attempting to affect the transition away from ICEVs. As the statistics from the survey responses revealed, the mean value of BEV knowledge among the 266 respondents was as high as 5.82 on the seven-point Likert scale. This value can partly be explained by approximately half of the respondents having owned a BEV. However, the average level of familiarity was so significant, that even the group of respondents who had never owned a BEV consequently also possessed well above neutral levels of knowledge and familiarity. In combination with the previously discussed relationship between knowledge and intention to adopt (as well as the perceived comparison to ICEVs), the results support the theory of the overall knowledge level in Norway being an important factor in the diffusion. To further strengthen the theory, one can compare the results to that of the study of Wang et al. in ten Chinese cities. In their study, the mean value of knowledge among the 320 respondents was only 2.75 on a five-point Likert scale, while adoptions rates are significantly lower than that of Norway (Wang et al., 2018). To further test this theory, a similar measurement could be performed in other countries proactively trying to diffuse BEVs.

A unique feature of the structural model in the study was that of the variable describing the perception of the strict comparison between BEVs and ICEVs as a vehicle alternative. The variable measured how consumers perceive BEVs compared to ICEVs in terms of performance, running costs, value, design and risks. The key difference between this variable and the adoption intentions variable, is that it does not relate to the financial incentives and measures taken by governments to tempt consumers to adopt BEVs. Interestingly, the results indicated that there was as well a strong and significant total effect of BEV knowledge on this perceived comparison (β= .65). The mean value of the comparison variable was 4.96 on the seven point Likert scale (higher values indicate higher evaluation of BEVs), compared to 5.74 in the adoption intention. This gap, however, is to be expected due to the mentioned factor of incentives. The finding of the of respondents average evaluation of BEVs being higher than of ICEVs might also have been influenced by the high share of respondents owning a BEV. However, the other half of the participants did not share this feature, making it a more weighted evaluation in this regard. Further, in combination with the Norwegian BEV adoption rate which was closing up on 50% in the first quarter of 2019, these results indicates that BEVs are progressively decreasing the gap on ICEVs in the minds of Norwegian consumers, and in some cases even surpassing them.

The second analysis concerned the effects of governmental incentives and charging networks on the intention to adopt BEVs. It is important to note, however, that the independent variable in this analysis does not correspond to the magnitude of issued incentives or actual density of charging networks. They correspond to how the measures are perceived by the population through satisfactory levels and familiarity. In sum, the results revealed the following: Familiarity with incentive policies and charging networks had a positive and significant effect on the adoption intentions as predicted in the hypothesis (β= .32 & .31). Further, the satisfactory levels with charging networks had no significant effect, while the satisfactory level with incentive policies had a positive and relatively strong effect compared to the awareness levels. It should also be noted that all these effects were significantly lower than that of knowledge on the IA variable.

However, as this analysis was only performed by linear regression due to the beforementioned complications, these results should not be weighted in the same way as the primary analysis. This is due to linear regression's several shortcomings, such as being restricted to binary linear relationships, sensitivity to outliers, and not being suited to explain complex concepts with multiple indicators (Montgomery, Peck, & Vining, 2012). This issue is also demonstrated by observing the low values of explained variance in the relationships. In other words, the indicators are only capable of explaining a small portion of the actual behaviour of the IA variable. It is, however, interesting to see that satisfactory levels with charging networks had no effect, while knowledge had a significantly higher effect than that of the other independent variables. Further, the explained variance of 30% which knowledge had on the IA variable should be noted.

A third and last analysis regressed the demographic profiles on the adoption intentions. This revealed that age had no significant effect on the IA variable, which contradicts the belief that young age relates to the embracing of green products (Sovacool, Kester, Noel, & de Rubens, 2018). However, it is possible that this was balanced out by higher salaries (which naturally follows age) as BEVs often has high investment costs. Further, higher educational levels had a small (β= .21), yet significant effect on the IA variable, which relates well to previous studies on this phenomena. Lastly, the regression analysis from gender also had a small (β= .25) and significant effect, where males were more likely to intend to adopt BEVs.

6.1.2 Potential Bias

In this sub-chapter, the potential biases which could interfere with the result's validity will be discussed. Firstly from the perspective of respondents which could occur due to the survey design or the data collection method. Then the biases from the researchers perspective will be discussed

6.1.2.1 Respondent's Bias

6.1.2.1.1 Common Method Bias

Common method bias occurs when variations in responses are caused by the instrument rather than the actual predispositions of respondents. On a broad level, this concerns halo effects, leniency effects, acquiescence (yea- and nay-saying) as well as social desirability. Due to the nature of this research, the last two are most relevant to consider.

Although acquiescence bias typically occurs in face-to-face interviews (for instance when a respondent assumes the interviewer is an expert and agrees by default with what the interviewer is saying), it could as well happen in questionnaire studies. Particularly when respondents feel pressured towards submitting a response this phenomena is likely to occur as they have no interest in participating. To avoid this, our study involved a non-rewarding online questionnaire survey where participation occurred through proactivity from respondents (e.g. finding and clicking the link). In addition, measures were taken to frame questions so that there were no "right" answers. Social desirability, on the other hand, is a more serious concern as the study concerns environmentally friendly technologies. However, measures were taken to limit this potential bias. These involved informing respondents that their respondents were completely anonymous, performing a pilot survey, as well as communicating with respondents and qualified professionals regarding framing (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

To further assess the level of common method bias, Harman's single factor test was performed on the items making up the survey. The method which is still commonly used today loads all items into a common factor and measures the total variance. According to Harmon, this total explained variance should be lower than 50% for common method bias to not interfering with the results. As presented in the results chapter, the study passed this test (43%). Further, to remove statistical outliers (which also could have occurred due to common method bias), a Mahalanobis distance analysis was performed, and outliers excluded. Based on these results and measures, common method bias should not be an issue when evaluating the results (Izenman et al., 1978; Podsakoff et al., 2003).

6.1.2.1.2 Habituation bias

Another respondents bias which should be considered is the habituation bias. This is the bias that occurs when respondents give similar answers to questions that are framed similarly. In the survey design, this issue was mostly avoided through the mentioned framing strategy, with the exception of the items making up the latent variable of Perceived Usefulness(PU). A way of assessing this bias is through the internal consistency of the items as a group (Cronbach's Alpha). This was performed through the reliability analysis presented in the results, which showed that the PU variable had the lowest Cronbach's Alpha among the latent variables (0.71). Based on this value, it is unlikely that habituation had a significant effect. However, it cannot be guaranteed that it did not occur for some of the respondents (Survey Methods, 2018).

6.1.2.2 Researcher's Bias

6.1.2.2.1 Selection Bias

Selection bias is introduced when the selection of individuals is not based on proper randomization. As previously discussed in the data collection chapter, the sampling occurred through a combination of convenience and snowball sampling due to the limited available resources. In other words, the sample was not based on proper randomization and selection bias could be a concern when evaluating the results. In order to control the sample to some extent, a demographic profile was required to be filled in by respondents. This revealed that the sample consisted of a good range in terms of age and educational levels, and in this regard, the sample was a good representation. The profiles also revealed that an overweight of males (68%) attended the survey, which reduces the generalizability of the study to some extent. Lastly, the demographic profile revealed that 54% of the respondents owned or had owned a BEV in the past. This is not a good representation of the population and was likely caused by potential respondents who were familiar with BEVs showing a higher interest in participating in the survey (Berk, 1983).

When evaluating the analysis, this selection bias first and foremost means that the results can not directly be generalized for the average Norwegian resident. It also means is that it was likely to be a higher level of familiarity in the sample than that of the actual population average. Further, in terms of the intention to adopt BEVs, the variable relates to "re-adopting" for approximately half the sample as they will not be purchasing a BEV for the first time.

6.1.2.2.2 Question-Order Bias

As the title suggests, this bias is introduced by the order the questions are presented to a respondent. This type of bias has been known to influence survey research for decades and is caused due to the human brain's tendency to organize information in patterns. This bias is particularly an issue when respondents are asked to evaluate different alternatives. In such a scenario, the second alternative is likely to be evaluated relative to the first, and not the actual opinion. In our case, this first and foremost relates to the final questions making up the comparison to ICEVs (CI) variable. The questions prior to this relate to the intention to adopt a BEV (IA) among the respondents. For respondents with a high degree of IA, it is possible that it positively influences the CI, as the respondent has expressed positive opinions of BEVs. Further, this bias might have influenced the IA variable in cases where positive opinions have been expressed prior to the items making up the variable such as a positive attitude (Israel & Taylor, 1990).

One way of limiting question-order bias is to randomize the question order in the survey. As this option was not available in the utilized tools, other measures had to be considered. A measure taken was that of asking general questions before specific questions, which is known to limit this issue. This is why the more specific questions of intention to adopt and comparison to ICEVs are presented at the end of the survey. However, the bias of question order should be considered as the question order was not randomized (QUIRKS, 2015).

6.1.2.2.3 Confirmation Bias

Another type of bias which needs to be addressed when working with social research is confirmation bias. This occurs when a researcher forms a hypothesis and uses responder's information to confirm beliefs while disregarding evidence that doesn't support the hypothesis. This problem is usually more relevant in qualitative analysis, as interpretation is more dependent on the researcher than the tools utilized. In qualitative research of the nature of our study, a hypothesis is developed in the form of a structural model prior to the research. The model is then analysed strictly through the SEM tool, with little to no possibility for the researcher to influence the results. The only influence the researcher had on the outcome of the actual analysis is to make changes to the original structural model during the analysis (Nickerson, 1998).

This particular scenario has already been discussed in the results chapter, where the model was "changed" in the sense of removing direction arrows in the structural model due to redundancy. This was done as the SEM tool indicated that certain effects occurred primarily through mediation, rather than direct effects. However, what is interesting when evaluating the hypothesis is the total effects among the latent variables. Hence, these "changes" did not influence the outcome of the analysis, it simply clarified that effects occurred through mediation when presenting the results. In conclusion, conformation bias should not be an issue in the evaluation.

6.1.3 Bias Affecting the Results

When evaluating all the findings it is important to consider the bias discussed in this chapter. The two types of bias which are believed to have significantly influenced the results are that of selection bias and question-order bias. The selection bias has been addressed throughout the chapter, as the collection procedure led to a large share of previous and current BEV owners participated in the survey. Further, the question order might also have led to higher scores of the items making up the IA and CI variables. Combined, these biases were likely to cause larger effects among the latent variables in the structural model, and thus overestimate the significance of knowledge in the model. However, when considering the strength of the effects, it is our understanding that it is beyond doubt that the existence of the effects in the estimated model would withstand despite an adjustment in compliance with the bias.

6.2 Conclusion, Implications, Limitations and Further Research

6.2.1 Takeaway From The Project

Through a comprehensive questionnaire study combined with structural equation modelling, a study was performed in Norway to explore the factors that influence consumers in the ongoing agenda of transitioning the automobile industry towards battery electric vehicles. The overall objective of the study was to introduce the factor of consumers' knowledge of the vehicles and technology when analysing the variables believed to affect the intention to adopt BEVs.

The results of the analysis confirmed that there is a strong and positive effect of consumers' knowledge on the purchase intention. This effect occurred through mediation of reducing risk perception, increasing the perceived usefulness and improving the overall attitude of BEVs and its technology. The results further revealed that knowledge had a strong and positive effect on the perceived side-by-side comparison between BEVs and ICEVs in terms of better value, performance and lower risks. This last finding is particularly interesting as it indicates that BEVs are catching up, and (in some cases) even surpassing ICEVs as a vehicle alternative when consumers gain knowledge of BEVs. The analysis also revealed that the level BEV knowledge among Norwegian consumers are very high. Combined with the effects of knowledge on adoption intentions, the results indicate that this functions as a driver to the Norwegian success in BEV diffusion.

Further, the analysis confirmed that perceived risks could be a psychological barrier against accepting and adopting BEVs. This lines up well with the previous research which revealed that risk perception is a considerable diffusion barrier when dealing with renewable energy solutions. This barrier, however, was significantly reduced in accordance with increasing levels of consumers' BEV knowledge. In other words, the analysis show that knowledge among consumers could significantly reduce the influence of one of the key barriers against diffusion.

The study also complements and contributes to TAM literature by verifying the proposed relationships among the original variables as well as adding new variables to the model. In line with Davis' original model, perceived usefulness and particularly attitude were also found be strongly related to the intention to use BEVs. In addition, the analysis showed that both knowledge and risk perception can function as a good fit in extended technology acceptance models. These features might be applicable to other studies involving technology acceptance.

Further, the study aimed to analyse the importance of government incentives and charging network compared to consumers knowledge. Due to complications with the internal reliability of the variables concerning governmental involvement, these factors could not be included in the structural equation modelling and the study was thus less conclusive in this regard. However, through a linear regression analysis it was found that satisfactory levels with charging networks and fiscal incentives, as well as incentive familiarity, had a positive effect on the adoption intentions in line with the expectations. It should also be noted that these effects were significantly lower than that of consumer's knowledge and familiarity with BEVs.

Lastly, a demographic regression analysis revealed that age had no significant effect on the adoption intentions among the sample. Education, however, had a weak yet significant impact where higher levels of education led to higher levels of purchase intentions. Similarly, gender was revealed to influence the intentions where males were more likely to be interested in purchasing a BEV than women.

6.2.2 Managerial Implications

The main takeaway from this study is that consumers' knowledge of BEVs should be taken into consideration when attempting to manage the adoption of the green vehicles. Norway has succeeded in diffusing knowledge of BEVs within its population, and this might be part of the explanation for their disproportionally large adoption rates compared to other salient actors. The recommendation based on the results in this research is therefore that governments aiming to substitute ICEVs with BEVs should take measures to spread information and educate potential adopters on BEVs and its technology. Achieving this would improve the overall attitude towards BEVs, increase the perceived usefulness and limit the existing risk barriers. In turn, this would increase consumers' willingness to adopt BEVs and contribute to the global task of creating a greener society.

Measures to achieve this could involve increased subsidising of research on BEVs and increase the publications regarding the topic on governmental and educational channels. A great example of this is the Norwegian governmentally supported statistical bureau "SSB". The well-reputed statistical bureau (which has been sited on several occasions in this thesis) publishes a large number of articles and surveys on BEVs on a regular basis. These articles, in turn, gets published on the main news channels which reaches a large part of the Norwegian population. Similarly, the governmentally supported automobile organization "NAF" is increasingly focused on electric vehicles and publishes articles on the topic on a regular basis. As these organizations holds a reliable reputation and reaches the mainstream media regularly, it is reasonable to assume they have contributed to the spread of BEV knowledge throughout the last three decades. Salient actors should therefore increase the support to research and publications regarding BEVs to achieve similar effects.

Another factor which should be considered in this aspect is the spread of misinformation. Many actors, particularly ICEV manufacturers, can benefit from damaging the reputation of BEVs. Therefore, one should be cautious about sources when publishing articles on this subject. In recent years, there have been several cases where articles has been published with the purpose of undermining the environmental importance of BEVs by for instance exaggerating the environmental footprint from battery production. This is an important issue to address, as the public perception of BEV's environmental impact is an important factor in the diffusion. Measures to avoid this should be made.

6.2.3 Retrospect and Limitations in Our Research

Despite the interesting findings in the analysis, the study had various limitations which are important to highlight. Firstly, the sample was not constructed through proper randomization due to the resources at hand. This limits the generalizability and validity of the results. Secondly, the factor of investment costs was not directly implemented into the framework, which could have enrichened the model by measuring this potential barrier against diffusion. Further, the research did not measure the actual adoption behaviour among the participants. Instead, the respondent's intentions were measured as performing a study of the actual behaviour would highly complicate the collection process and be based on previous actions rather than future behaviour. However, as the behavioural intention is the most direct antecedent of actual behaviour, this measurement still functions as a predictor for diffusion (Ajzen & Gilbert Cote, 2008). Lastly, the study was only performed in Norway, and the results could only be compared to that of the study in 10 Chinese cities led by Shanyong Wang (Wang et al., 2018). If a similar study was performed in other countries which actively tries to influence the diffusion, more concise conclusions could be made about knowledge's role in the ongoing agenda of the green transition in the automobile industry.

Concerning the collected data through the survey design, the author acknowledges that improvements could have been made. Firstly, as previously discussed, the items measuring the governmental incentives and charging networks should have been design differently to ensure sufficient internal reliability and good measurements. Splitting these variables into separate categories as well as developing a higher quantity of items would likely have solves the issues faced in the analysis. If this would have been achieved, the study could have made a clearer conclusion to the first sub-research question regarding the importance of consumers' knowledge compared to incentives and charging networks. Secondly, the survey could have been designed to collect a more comprehensive demographic profile of the participants. For instance, a feature which could have been included is the participants annual salaries. By including this, we could have analysed whether there is a correlation between income and intention to adopt BEVs and thus performed a more comprehensive demographic analysis.

6.2.4 Future Research

Our study was performed solely in the BEV pioneer Norway, and thus the generalizability of the study is limited. By performing a similar analysis in other locations, particularly other salient actors aiming to increase adoption rates, a more generalizable conclusion could be made. European countries like the Netherlands, Germany, Sweden, Denmark, Austria and the United Kingdom could be particularly interesting scopes of research as they all actively have attempted to spark the diffusion. Out of these, the author would find it particularly interesting to perform an analysis In the Netherlands as they, together with Norway, aims to ban ICEVs by 2030. It would therefore be interesting to look for factors, apart from incentives, which differs between the countries that might have led Norway to "lead this race" with close to 10 times as high adoption rates.

Another phenomena which would be interesting to investigate is the knowledge diffusion regarding BEVs. Our study clearly indicates that Norway has succeeded with educating its population on BEVs. To perform a study on the effectiveness of measures to spread knowledge of BEVs could therefore be very helpful to aid governments in the transition.

Bibliography

Ajzen, I., & Gilbert Cote, N. (2008). Attitudes and the prediction of behavior. In (pp. 289-311).

Berk, R. A. (1983). An Introduction to Sample Selection Bias in Sociological Data. *American Sociological Review, 48*(3), 386-398. doi:10.2307/2095230

Blunch, N. J. (2015). *Introduction to structural equation modeling using IBM SPSS statistics and EQS*: Sage.

Bovag. (2019). Registraties elektrische auto's in 2018 verdrievoudigd. Retrieved from https://mijn.bovag.nl/actueel/nieuws/2019/januari/registraties-elektrische-auto%E2%80%99s-in-2018-verdrievou

Consumer Federation of America. (2015). Knowledge Affects Consumer Interest in EVs, New EVs Guide to Address Info Gap. Retrieved from https://consumerfed.org/press_release/knowledge-affects-consumer-interest-in-evs-new-evs-guide-to-address-info-gap/

Davis, F., Bagozzi, R., & R. Warshaw, P. (1989). *User Acceptance of Computer Technology: A Comparison of Two Theoretical Models* (Vol. 35).

E24. (2019). Historisk elbilsalg i mars. Retrieved from https://e24.no/bil/elbil/historisk-elbilsalg-i-mars/24593986

Eisinga, R., Grotenhuis, M., & Pelzer, B. (2013). *The reliability of a two-item scale: Pearson, Cronbach, or Spearman-Brown?* (Vol. 58).

European Enviroment Agency. (2018). Electric vehicles as a proportion of the total fleet. Retrieved from https://www.eea.europa.eu/data-and-maps/indicators/proportion-of-vehicle-fleet-meeting-4/assessment-2#tab-related-briefings

European Enviroment Agency. (2019). Outdoor air quality in urban areas. Retrieved from https://www.eea.europa.eu/airs/2018/environment-and-health/outdoor-air-quality-urban-areas

EV-VOLUMES. (2019). Global EV Sales for 2018 – Final Results. Retrieved from http://www.ev-volumes.com/country/total-world-plug-in-vehicle-volumes/

Feder, G., & Slade, R. (1984). The Acquisition of Information and the Adoption of New Technology. *American Journal of Agricultural Economics, 66*(3), 312-320. doi:10.2307/1240798

Granovskii, M., Dincer, I., & Rosen, M. A. (2006). Economic and environmental comparison of conventional, hybrid, electric and hydrogen fuel cell vehicles. *Journal of Power Sources, 159*(2), 1186-1193. doi:https://doi.org/10.1016/j.jpowsour.2005.11.086

Ha, H. Y. (2012). Predicting consumer intentions to purchase energy-efficient products. *Journal of Consumer Marketing, 29*(7), 461-469. doi:10.1108/07363761211274974

Hagman, J., Ritzén, S., Stier, J. J., & Susilo, Y. (2016). Total cost of ownership and its potential implications for battery electric vehicle diffusion. *Research in Transportation Business & Management, 18*, 11-17. doi:https://doi.org/10.1016/j.rtbm.2016.01.003

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). Multivariate data analysis (Vol. 6). In: Upper Saddle River, NJ: Pearson Prentice Hall.

Hardman, S., Chandan, A., Tal, G., & Turrentine, T. (2017). The effectiveness of financial purchase incentives for battery electric vehicles – A review of the evidence. *Renewable and Sustainable Energy Reviews, 80*, 1100-1111. doi:https://doi.org/10.1016/j.rser.2017.05.255

Heffner, R. R., Kurani, K. S., & Turrentine, T. (2005). Effects of vehicle image in gasoline-hybrid electric vehicles.

Hooper, D., Coughlan, J., & R. Mullen, M. (2007). *Structural Equation Modeling: Guidelines for Determining Model Fit* (Vol. 6).

Iacobucci, D., & Duhachek, A. (2003). Advancing Alpha: Measuring Reliability With Confidence. *Journal of Consumer Psychology, 13*(4), 478-487. doi:https://doi.org/10.1207/S15327663JCP1304_14

Israel, G. D., & Taylor, C. L. (1990). Can response order bias evaluations? *Evaluation and Program Planning, 13*(4), 365-371. doi:https://doi.org/10.1016/0149-7189(90)90021-N

Izenman, A., H. Harman, H., G. Joreskog, K., E. Klovan, J., & Reyment, R. (1978). *Modern Factor Analysis, 3rd Edition Revised* (Vol. 73).

Jöreskog, K. G. (1969). A general approach to confirmatory maximum likelihood factor analysis. *Psychometrika, 34*(2), 183-202. doi:10.1007/BF02289343

Junquera, B., Moreno, B., & Álvarez, R. (2016). Analyzing consumer attitudes towards electric vehicle purchasing intentions in Spain: Technological limitations and vehicle confidence. *Technological Forecasting and Social Change, 109*, 6-14. doi:https://doi.org/10.1016/j.techfore.2016.05.006

Kaplan, S. (1991). Beyond rationality: Clarity-based decision making. In *Environment, cognition, and action: An integrated approach.* (pp. 171-190). New York, NY, US: Oxford University Press.

Kim, M.-K., Oh, J., Park, J.-H., & Joo, C. (2018). Perceived value and adoption intention for electric vehicles in Korea: Moderating effects of environmental traits and government supports. *Energy, 159*, 799-809. doi:https://doi.org/10.1016/j.energy.2018.06.064

Kline, R. B. (2015). *Principles and practice of structural equation modeling*: Guilford publications.

Laerd Statistics. (2018). Linear Regression Analysis using SPSS Statistics. Retrieved from https://statistics.laerd.com/spss-tutorials/linear-regression-using-spss-statistics.php

Lévay, P. Z., Drossinos, Y., & Thiel, C. (2017). The effect of fiscal incentives on market penetration of electric vehicles: A pairwise comparison of total cost of ownership. *Energy Policy, 105*, 524-533. doi:https://doi.org/10.1016/j.enpol.2017.02.054

Li, W., Long, R., Chen, H., & Geng, J. (2017). Household factors and adopting intention of battery electric vehicles: a multi-group structural equation model analysis among consumers in Jiangsu Province, China. *Natural Hazards, 87*(2), 945-960. doi:10.1007/s11069-017-2803-9

Lindgren, J., & Lund, P. D. (2016). Effect of extreme temperatures on battery charging and performance of electric vehicles. *Journal of Power Sources, 328*, 37-45. doi:https://doi.org/10.1016/j.jpowsour.2016.07.038

Ma, S.-C., Fan, Y., & Feng, L. (2017). An evaluation of government incentives for new energy vehicles in China focusing on vehicle purchasing restrictions. *Energy Policy, 110*, 609-618. doi:https://doi.org/10.1016/j.enpol.2017.07.057

Manly, C. A., & Wells, R. S. (2015). Reporting the Use of Multiple Imputation for Missing Data in Higher Education Research. *Research in Higher Education, 56*(4), 397-409. doi:10.1007/s11162-014-9344-9

Marangunić, N., & Granić, A. (2015). Technology acceptance model: a literature review from 1986 to 2013. *Universal Access in the Information Society, 14*(1), 81-95. doi:10.1007/s10209-014-0348-1

Montgomery, D. C., Peck, E. A., & Vining, G. G. (2012). *Introduction to linear regression analysis* (Vol. 821): John Wiley & Sons.

Nadri, H., Rahimi, B., Lotfnezhad Afshar, H., Samadbeik, M., & Garavand, A. (2018). *Factors Affecting Acceptance of Hospital Information Systems Based on Extended Technology Acceptance Model: A Case Study in Three Paraclinical Departments* (Vol. 09).

Netherlands Enterprice Agency. (2018). Statistics Electric Vehicles in the Netherlands. Retrieved from https://www.rvo.nl/sites/default/files/2018/09/2018_08_Statistics%20Electric%20Vehicles%20and%20Charging%20in%20The%20Netherlands%20up%20to%20and%20including%20August%202018.pdf

Nickerson, R. S. (1998). Confirmation Bias: A Ubiquitous Phenomenon in Many Guises. *Review of General Psychology, 2*(2), 175-220. doi:10.1037/1089-2680.2.2.175

Ogbeide, O. (2015). *Consumer behaviour in product acquisition: Literature review* (Vol. 15).

Oliver, J. D., & Rosen, D. E. (2010). Applying the Environmental Propensity Framework: A Segmented Approach to Hybrid Electric Vehicle Marketing Strategies. *Journal of Marketing Theory and Practice, 18*(4), 377-393. doi:10.2753/MTP1069-6679180405

Park, E., & Ohm, J. Y. (2014). Factors influencing the public intention to use renewable energy technologies in South Korea: Effects of the Fukushima nuclear accident. *Energy Policy, 65*, 198-211. doi:https://doi.org/10.1016/j.enpol.2013.10.037

Peterson, R. A., & Kim, Y. (2013). On the relationship between coefficient alpha and composite reliability. *J Appl Psychol, 98*(1), 194-198. doi:10.1037/a0030767

Pfaffenbichler, P., Fearnley, N., Figenbaum, E., & Jellinek, R. (2015). *E-vehicle policies and incentives - assessment and recommendations*.
Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879-903. doi:10.1037/0021-9010.88.5.879
Qian, L., & Yin, J. (2017). Linking Chinese cultural values and the adoption of electric vehicles: The mediating role of ethical evaluation. *Transportation Research Part D: Transport and Environment, 56*, 175-188. doi:https://doi.org/10.1016/j.trd.2017.07.029
QUIRKS. (2015). 9 types of research bias and how to avoid them. Retrieved from https://www.quirks.com/articles/9-types-of-research-bias-and-how-to-avoid-them
She, Z.-Y., Qing Sun, Ma, J.-J., & Xie, B.-C. (2017). What are the barriers to widespread adoption of battery electric vehicles? A survey of public perception in Tianjin, China. *Transport Policy, 56*, 29-40. doi:https://doi.org/10.1016/j.tranpol.2017.03.001
Sierzchula, W., Bakker, S., Maat, K., & van Wee, B. (2014). The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy, 68*, 183-194. doi:https://doi.org/10.1016/j.enpol.2014.01.043
Söderlund, M. (2002). Customer familiarity and its effects on satisfaction and behavioral intentions. *Psychology & Marketing, 19*(10), 861-879. doi:10.1002/mar.10041
Sovacool, B. K., Kester, J., Noel, L., & de Rubens, G. Z. (2018). The demographics of decarbonizing transport: The influence of gender, education, occupation, age, and household size on electric mobility preferences in the Nordic region. *Global Environmental Change, 52*, 86-100. doi:https://doi.org/10.1016/j.gloenvcha.2018.06.008
Statistics Solutions. (2013). What is Linear Regression? Retrieved from https://www.statisticssolutions.com/what-is-linear-regression/
Statistisk Sentralbyra. (2017). 13 elbiler per ladepunkt. Retrieved from https://www.ssb.no/natur-og-miljo/artikler-og-publikasjoner/13-elbiler-per-ladepunkt
Statistisk Sentralbyra. (2019). Bilparken. Retrieved from https://www.ssb.no/transport-og-reiseliv/statistikker/bilreg
Steinhilber, S., Wells, P., & Thankappan, S. (2013). Socio-technical inertia: Understanding the barriers to electric vehicles. *Energy Policy, 60*, 531-539. doi:https://doi.org/10.1016/j.enpol.2013.04.076
Stoneman, P., & Diederen, P. (1994). Technology Diffusion and Public Policy. *The Economic Journal, 104*(425), 918-930. doi:10.2307/2234987
Survey Methods. (2018). How Habituation Can Negatively Affect Your Survey Responses. Retrieved from https://surveymethods.com/blog/how-habituation-can-negatively-affect-your-survey-responses/
TGE. (2019). Technology Acceptance Model information systems theory. Retrieved from https://techgadgets.expert/technology-acceptance/
Tietge, U., Mock, P., Lutsey, N., & Campestrini, A. (2016). *Comparison of leading electric vehicle policy and deployment in Europe*.
Trading Economics. (2019). Norway - Population density Retrieved from https://tradingeconomics.com/norway/population-density-people-per-sq-km-wb-data.html
Ullman, J. (2006). *Structural Equation Modeling: Reviewing the Basics and Moving Forward* (Vol. 87).
Wang, S., Wang, J., Li, J., Wang, J., & Liang, L. (2018). Policy implications for promoting the adoption of electric vehicles: Do consumer's knowledge, perceived risk and financial incentive policy matter? *Transportation Research Part A: Policy and Practice, 117*, 58-69. doi:https://doi.org/10.1016/j.tra.2018.08.014
Wiedmann, K.-P., Hennigs, N., Pankalla, L., Kassubek, M., & Seegebarth, B. (2011). Adoption barriers and resistance to sustainable solutions in the automotive sector. *Journal of Business Research, 64*(11), 1201-1206. doi:https://doi.org/10.1016/j.jbusres.2011.06.023
Wright, S. (1934). The Method of Path Coefficients. *The Annals of Mathematical Statistics, 5*(3), 161-215. Retrieved from http://www.jstor.org/stable/2957502

Zografakis, N., Sifaki, E., Pagalou, M., Nikitaki, G., Psarakis, V., & Tsagarakis, K. P. (2010). Assessment of public acceptance and willingness to pay for renewable energy sources in Crete. *Renewable and Sustainable Energy Reviews, 14*(3), 1088-1095. doi:https://doi.org/10.1016/j.rser.2009.11.009

Appendices

Appendix A – Common Method Bias (output SPSS)

```
FACTOR
  /VARIABLES AI1 AI2 IP1 IP2 KB1 KB2 KB3 PR1 PR2 PR3 PR4 PU1 PU2 PU3 AB1 AB
2 AB3 IA1 IA2 IA4 CI1
    CI2 CI3
  /MISSING LISTWISE
  /ANALYSIS AI1 AI2 IP1 IP2 KB1 KB2 KB3 PR1 PR2 PR3 PR4 PU1 PU2 PU3 AB1 AB2
 AB3 IA1 IA2 IA4 CI1 CI2
    CI3
  /PRINT INITIAL EXTRACTION
  /CRITERIA FACTORS(1) ITERATE(25)
  /EXTRACTION PAF
  /ROTATION NOROTATE
  /METHOD=CORRELATION
```

Factor Analysis

Communalities

	Initial	Extraction
AI1	.494	.222
AI2	.495	.192
IP1	.356	.253
IP2	.314	3.172E-5
KB1	.658	.389
KB2	.716	.459
KB3	.660	.474
PR1	.393	.215
PR2	.587	.470
PR3	.478	.297
PR4	.594	.452
PU1	.484	.253
PU2	.418	.292
PU3	.641	.451
AB1	.671	.574
AB2	.822	.784
AB3	.702	.540
IA1	.845	.716
IA2	.840	.692
IA4	.851	.738
CI1	.680	.620
CI2	.529	.369
CI3	.655	.589

Extraction Method: Principal
Axis Factoring.

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	10.515	45.716	45.716	10.038	43.644	43.644
2	2.181	9.483	55.199			
3	1.401	6.090	61.289			
4	1.139	4.951	66.240			
5	.964	4.192	70.432			
6	.858	3.729	74.161			
7	.723	3.142	77.303			
8	.616	2.679	79.982			
9	.522	2.269	82.251			
10	.499	2.170	84.421			
11	.494	2.149	86.570			
12	.451	1.960	88.531			
13	.385	1.675	90.206			
14	.335	1.456	91.662			
15	.320	1.390	93.051			
16	.298	1.297	94.348			
17	.259	1.128	95.476			
18	.234	1.019	96.495			
19	.230	1.000	97.494			
20	.213	.925	98.419			
21	.159	.691	99.111			
22	.113	.493	99.603			
23	.091	.397	100.000			

Extraction Method: Principal Axis Factoring.

Factor Matrix[a]

	Factor
	1
AI1	.471
AI2	.438
IP1	.503
IP2	-.006
KB1	.623
KB2	.677
KB3	.688
PR1	-.464
PR2	-.685
PR3	-.545
PR4	-.672
PU1	.503
PU2	.540
PU3	.671
AB1	.758
AB2	.885
AB3	.735
IA1	.846
IA2	.832
IA4	.859
CI1	.788
CI2	.607
CI3	.768

Extraction Method: Principal Axis Factoring.

a. 1 factors extracted. 4 iterations required.

Appendix B – Descriptive Statistics in Structural Model (output SPSS)

```
REGRESSION
 /DESCRIPTIVES MEAN STDDEV CORR SIG N
 /MISSING LISTWISE
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT ID
 /METHOD=ENTER KB_AV IA_AV PU_av AB_av PR_av CI_av.
```

Regression

Descriptive Statistics

	Mean	Std. Deviation	N
ID	140.68	85.004	266
KB_AV	5.8208	1.32484	266
IA_AV	5.7368	1.63917	266
PU_av	5.3697	1.27117	266
AB_av	5.2882	1.60856	266
PR_av	3.1504	1.41336	266
CI_av	4.9574	1.38298	266

Correlations

		ID	KB_AV	IA_AV	PU_av	AB_av	PR_av
Pearson Correlation	ID	1.000	-.139	-.121	-.165	-.075	.159
	KB_AV	-.139	1.000	.607	.479	.620	-.563
	IA_AV	-.121	.607	1.000	.597	.896	-.688
	PU_av	-.165	.479	.597	1.000	.671	-.512
	AB_av	-.075	.620	.896	.671	1.000	-.673
	PR_av	.159	-.563	-.688	-.512	-.673	1.000
	CI_av	-.176	.569	.759	.655	.772	-.665
Sig. (1-tailed)	ID	.	.012	.025	.003	.110	.005
	KB_AV	.012	.	.000	.000	.000	.000
	IA_AV	.025	.000	.	.000	.000	.000
	PU_av	.003	.000	.000	.	.000	.000
	AB_av	.110	.000	.000	.000	.	.000
	PR_av	.005	.000	.000	.000	.000	.
	CI_av	.002	.000	.000	.000	.000	.000
N	ID	266	266	266	266	266	266
	KB_AV	266	266	266	266	266	266
	IA_AV	266	266	266	266	266	266
	PU_av	266	266	266	266	266	266

Correlations

		CI_av
Pearson Correlation	ID	-.176
	KB_AV	.569
	IA_AV	.759
	PU_av	.655
	AB_av	.772
	PR_av	-.665
	CI_av	1.000
Sig. (1-tailed)	ID	.002
	KB_AV	.000
	IA_AV	.000
	PU_av	.000
	AB_av	.000
	PR_av	.000
	CI_av	.
N	ID	266
	KB_AV	266
	IA_AV	266
	PU_av	266

Correlations

		ID	KB_AV	IA_AV	PU_av	AB_av	PR_av
	AB_av	266	266	266	266	266	266
	PR_av	266	266	266	266	266	266
	CI_av	266	266	266	266	266	266

Correlations

		CI_av
	AB_av	266
	PR_av	266
	CI_av	266

Appendix C – Scale Reliability Structural Model (output SPSS)

```
RELIABILITY
  /VARIABLES=KB1 KB2 KB3
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=SCALE.
```

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	266	100.0
	Excluded[a]	0	.0
	Total	266	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.895	3

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
17.46	15.797	3.975	3

```
RELIABILITY
  /VARIABLES=PR1 PR2 PR3 PR4
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=SCALE.
```

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	266	100.0
	Excluded[a]	0	.0
	Total	266	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.804	4

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
12.60	31.961	5.653	4

```
RELIABILITY
  /VARIABLES=PU1 PU2 PU3
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=SCALE.
```

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	266	100.0
	Excluded[a]	0	.0
	Total	266	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.733	3

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
16.11	14.543	3.814	3

```
RELIABILITY
  /VARIABLES=AB1 AB2 AB3
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=SCALE.
```

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	266	100.0
	Excluded[a]	0	.0
	Total	266	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.869	3

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
15.86	23.287	4.826	3

```
RELIABILITY
  /VARIABLES=IA1 IA2 IA4
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=SCALE.
```

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	266	100.0
	Excluded[a]	0	.0
	Total	266	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.945	3

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
17.06	25.320	5.032	3

```
RELIABILITY
  /VARIABLES=IP1 IP2
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=SCALE.
```

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	228	85.7
	Excluded[a]	38	14.3
	Total	266	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.402	2

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
8.88	6.087	2.467	2

```
RELIABILITY
  /VARIABLES=AI1 AI2
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=SCALE.
```

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	266	100.0
	Excluded[a]	0	.0
	Total	266	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.714	2

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
11.30	5.564	2.359	2

```
RELIABILITY
  /VARIABLES=CI1 CI2 CI3
  /SCALE('ALL VARIABLES') ALL
```

```
/MODEL=ALPHA
/STATISTICS=SCALE.
```

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	266	100.0
	Excluded[a]	0	.0
	Total	266	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.854	3

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
14.87	17.214	4.149	3

```
 GET
  FILE='C:\Users\alesa\Downloads\311 før det går galt\311.Reduced.266.Corre
ct.sav'.
DATASET NAME DataSet1 WINDOW=FRONT.
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT IA_AV
  /METHOD=ENTER GenderNOM AgeGroupesNom EDU035.
```

Regression

Notes

Output Created		09-JUL-2019 00:30:48
Comments		
Input	Data	C:\Users\alesa\Downloads\311 før det går galt\311.Reduced.266.Correct.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	266
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any variable used.

Notes

Syntax		REGRESSION /DESCRIPTIVES MEAN STDDEV CORR SIG N /MISSING LISTWISE /STATISTICS COEFF OUTS CI(95) R ANOVA CHANGE /CRITERIA=PIN(.05) POUT(.10) /NOORIGIN /DEPENDENT IA_AV /METHOD=ENTER GenderNOM AgeGroupesNom EDU035.
Resources	Processor Time	00:00:00.02
	Elapsed Time	00:00:00.02
	Memory Required	5856 bytes
	Additional Memory Required for Residual Plots	0 bytes

```
[DataSet1] C:\Users\alesa\Downloads\311 før det går galt\311.Reduced.266.Co
rrect.sav
```

Descriptive Statistics

	Mean	Std. Deviation	N
IA_AV	5.7368	1.63917	266
GenderNOM	.6805	.46718	266
AgeGroupesNom	3.6203	.97642	266
EDU035	2.6353	2.07012	266

Correlations

		IA_AV	GenderNOM	AgeGroupesNom	EDU035
Pearson Correlation	IA_AV	1.000	.246	-.073	.208
	GenderNOM	.246	1.000	-.035	.059
	AgeGroupesNom	-.073	-.035	1.000	.090
	EDU035	.208	.059	.090	1.000
Sig. (1-tailed)	IA_AV	.	.000	.118	.000
	GenderNOM	.000	.	.283	.171
	AgeGroupesNom	.118	.283	.	.072
	EDU035	.000	.171	.072	.
N	IA_AV	266	266	266	266
	GenderNOM	266	266	266	266
	AgeGroupesNom	266	266	266	266
	EDU035	266	266	266	266

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	EDU035, GenderNOM, AgeGroupesNom[b]	.	Enter

a. Dependent Variable: IA_AV

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	Change Statistics: F Change
1	.324[a]	.105	.095	1.55965	.105	10.237

Model Summary

Model	Change Statistics: df1	Change Statistics: df2	Change Statistics: Sig. F Change
1	3	262	.000

a. Predictors: (Constant), EDU035, GenderNOM, AgeGroupesNom

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	74.705	3	24.902	10.237	.000[b]
	Residual	637.318	262	2.433		
	Total	712.023	265			

a. Dependent Variable: IA_AV

b. Predictors: (Constant), EDU035, GenderNOM, AgeGroupesNom

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	5.267	.406		12.963	.000
	GenderNOM	.812	.206	.231	3.950	.000
	AgeGroupesNom	-.139	.099	-.083	-1.410	.160
	EDU035	.160	.047	.202	3.429	.001

Coefficients[a]

Model		95.0% Confidence Interval for B	
		Lower Bound	Upper Bound
1	(Constant)	4.467	6.067
	GenderNOM	.407	1.217
	AgeGroupesNom	-.333	.055
	EDU035	.068	.251

a. Dependent Variable: IA_AV

Appendix E – Descriptive Statistics and Results Government involvement (output SPSS)

```
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT IA2
  /METHOD=ENTER KB_AV AI1 AI2 IP1 IP2
  /SCATTERPLOT=(*ZRESID ,*ZPRED)
  /RESIDUALS NORMPROB(ZRESID) .
```

```
Results of regression analysis (demographic profile)
```

Regression

Descriptive Statistics

	Mean	Std. Deviation	N
IA2	5.88	1.686	213
KB_AV	6.0407	1.12826	213
AI1	6.29	.994	213
AI2	5.47	1.298	213
IP1	5.29	1.622	213
IP2	3.62	1.496	213

Correlations

		IA2	KB_AV	AI1	AI2	IP1	IP2
Pearson Correlation	IA2	1.000	.548	.297	.305	.415	-.097
	KB_AV	.548	1.000	.625	.557	.501	.090
	AI1	.297	.625	1.000	.530	.402	.159
	AI2	.305	.557	.530	1.000	.348	.336
	IP1	.415	.501	.402	.348	1.000	.232
	IP2	-.097	.090	.159	.336	.232	1.000
Sig. (1-tailed)	IA2	.	.000	.000	.000	.000	.079
	KB_AV	.000	.	.000	.000	.000	.095
	AI1	.000	.000	.	.000	.000	.010
	AI2	.000	.000	.000	.	.000	.000
	IP1	.000	.000	.000	.000	.	.000
	IP2	.079	.095	.010	.000	.000	.
N	IA2	213	213	213	213	213	213
	KB_AV	213	213	213	213	213	213
	AI1	213	213	213	213	213	213
	AI2	213	213	213	213	213	213
	IP1	213	213	213	213	213	213
	IP2	213	213	213	213	213	213

```
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT IA2
  /METHOD=ENTER KB_AV
  /SCATTERPLOT=(*ZRESID ,*ZPRED)
  /RESIDUALS NORMPROB(ZRESID) .
```

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	KB_AV[b]	.	Enter

a. Dependent Variable: IA2

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.548[a]	.300	.297	1.414

a. Predictors: (Constant), KB_AV

b. Dependent Variable: IA2

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	181.075	1	181.075	90.591	.000[b]
	Residual	421.751	211	1.999		
	Total	602.826	212			

a. Dependent Variable: IA2

b. Predictors: (Constant), KB_AV

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.930	.529		1.758	.080
	KB_AV	.819	.086	.548	9.518	.000

Coefficients[a]

Model		95.0% Confidence Interval for B	
		Lower Bound	Upper Bound
1	(Constant)	-.113	1.972
	KB_AV	.649	.989

a. Dependent Variable: IA2

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.75	6.66	5.88	.924	213
Residual	-5.118	3.067	.000	1.410	213
Std. Predicted Value	-4.468	.850	.000	1.000	213
Std. Residual	-3.620	2.169	.000	.998	213

a. Dependent Variable: IA2

```
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT IA2
  /METHOD=ENTER AI1
  /SCATTERPLOT=(*ZRESID ,*ZPRED)
  /RESIDUALS NORMPROB(ZRESID) .
```

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	AI1[b]	.	Enter

a. Dependent Variable: IA2

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.297[a]	.088	.084	1.614

a. Predictors: (Constant), AI1

b. Dependent Variable: IA2

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	53.066	1	53.066	20.367	.000[b]
	Residual	549.761	211	2.606		
	Total	602.826	212			

a. Dependent Variable: IA2

b. Predictors: (Constant), AI1

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2.714	.710		3.825	.000
	AI1	.503	.112	.297	4.513	.000

Coefficients[a]

Model		95.0% Confidence Interval for B Lower Bound	Upper Bound
1	(Constant)	1.315	4.113
	AI1	.283	.723

a. Dependent Variable: IA2

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	3.22	6.24	5.88	.500	213
Residual	-5.237	2.273	.000	1.610	213
Std. Predicted Value	-5.317	.718	.000	1.000	213
Std. Residual	-3.244	1.408	.000	.998	213

a. Dependent Variable: IA2

```
REGRESSION
 /DESCRIPTIVES MEAN STDDEV CORR SIG N
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS CI(95) R ANOVA
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT IA2
 /METHOD=ENTER AI2
 /SCATTERPLOT=(*ZRESID ,*ZPRED)
 /RESIDUALS NORMPROB(ZRESID) .
```

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	AI2[b]	.	Enter

a. Dependent Variable: IA2

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.305[a]	.093	.088	1.610

a. Predictors: (Constant), AI2

b. Dependent Variable: IA2

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	55.932	1	55.932	21.579	.000[b]
	Residual	546.894	211	2.592		
	Total	602.826	212			

a. Dependent Variable: IA2

b. Predictors: (Constant), AI2

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3.711	.479		7.745	.000
	AI2	.396	.085	.305	4.645	.000

Coefficients[a]

Model		95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound
1	(Constant)	2.767	4.656
	AI2	.228	.564

a. Dependent Variable: IA2

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	4.11	6.48	5.88	.514	213
Residual	-5.086	2.497	.000	1.606	213
Std. Predicted Value	-3.447	1.176	.000	1.000	213
Std. Residual	-3.159	1.551	.000	.998	213

a. Dependent Variable: IA2

```
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT IA2
  /METHOD=ENTER IP1
  /SCATTERPLOT=(*ZRESID ,*ZPRED)
  /RESIDUALS NORMPROB(ZRESID) .
```

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	IP1[b]	.	Enter

a. Dependent Variable: IA2

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.415[a]	.172	.168	1.538

a. Predictors: (Constant), IP1

b. Dependent Variable: IA2

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	103.697	1	103.697	43.837	.000[b]
	Residual	499.129	211	2.366		
	Total	602.826	212			

a. Dependent Variable: IA2

b. Predictors: (Constant), IP1

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.598	.360		9.992	.000
	IP1	.431	.065	.415	6.621	.000

Coefficients[a]

Model		95.0% Confidence Interval for B	
		Lower Bound	Upper Bound
1	(Constant)	2.888	4.308
	IP1	.303	.560

a. Dependent Variable: IA2

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	4.03	6.62	5.88	.699	213
Residual	-5.617	2.539	.000	1.534	213
Std. Predicted Value	-2.643	1.057	.000	1.000	213
Std. Residual	-3.652	1.651	.000	.998	213

a. Dependent Variable: IA2

```
REGRESSION
 /DESCRIPTIVES MEAN STDDEV CORR SIG N
 /MISSING LISTWISE
 /STATISTICS COEFF OUTS CI(95) R ANOVA
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
```

```
/DEPENDENT IA2
/METHOD=ENTER IP2
/SCATTERPLOT=(*ZRESID ,*ZPRED)
/RESIDUALS NORMPROB(ZRESID) .
```

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	IP2[b]	.	Enter

a. Dependent Variable: IA2

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.097[a]	.009	.005	1.682

a. Predictors: (Constant), IP2

b. Dependent Variable: IA2

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.678	1	5.678	2.006	.158[b]
	Residual	597.149	211	2.830		
	Total	602.826	212			

a. Dependent Variable: IA2

b. Predictors: (Constant), IP2

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	6.274	.302		20.743	.000
	IP2	-.109	.077	-.097	-1.416	.158

Coefficients[a]

Model		95.0% Confidence Interval for B Lower Bound	Upper Bound
1	(Constant)	5.678	6.870
	IP2	-.262	.043

a. Dependent Variable: IA2

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	5.51	6.16	5.88	.164	213
Residual	-5.165	1.492	.000	1.678	213
Std. Predicted Value	-2.260	1.752	.000	1.000	213
Std. Residual	-3.070	.887	.000	.998	213

a. Dependent Variable: IA2

Appendix F – STD total effects in Estimated Model (output AMOS)

Standardized Total Effects (Group number 1 - Default model)

	KB	PR	PU	AB
PR	-.666	.000	.000	.000
PU	.606	-.477	.000	.000
AB	.685	-.624	.516	.000
CI	.647	-.670	.529	.398
IA	.663	-.629	.316	1.266
CI_SUM	.597	-.619	.488	.367
IA_SUM	.644	-.611	.307	1.231
AB_SUM	.639	-.582	.481	.932
PU_SUM	.518	-.408	.855	.000
PR_SUM	-.597	.896	.000	.000
KB_SUM	.945	.000	.000	.000

Standardized Total Effects (Group number 1 - Default model)

Standardized Total Effects - Lower Bounds (BC) (Group number 1 - Default model)

	KB	PR	PU	AB
PR	-.773	.000	.000	.000
PU	.457	-.682	.000	.000
AB	.582	-.772	.331	.000
CI	.547	-.796	.362	.131
IA	.567	-.765	.123	1.097
CI_SUM	.500	-.746	.337	.123
IA_SUM	.551	-.747	.120	1.067
AB_SUM	.545	-.729	.311	.917
PU_SUM	.390	-.581	.827	.000
PR_SUM	-.699	.881	.000	.000
KB_SUM	.932	.000	.000	.000

Standardized Total Effects - Upper Bounds (BC) (Group number 1 - Default model)

	KB	PR	PU	AB
PR	-.545	.000	.000	.000
PU	.709	-.265	.000	.000
AB	.771	-.480	.696	.000
CI	.730	-.511	.724	.675
IA	.757	-.472	.488	1.594
CI_SUM	.674	-.483	.664	.631
IA_SUM	.735	-.459	.476	1.544
AB_SUM	.721	-.447	.646	.943
PU_SUM	.611	-.225	.878	.000
PR_SUM	-.486	.911	.000	.000
KB_SUM	.955	.000	.000	.000

Standardized Total Effects - Two Tailed Significance (BC) (Group number 1 - Default model)

	KB	PR	PU	AB
PR	.003	...	...	...
PU	.009	.004	...	...
AB	.004	.004	.010	...
CI	.007	.005	.007	.006
IA	.003	.007	.008	.010
CI_SUM	.007	.004	.007	.006
IA_SUM	.003	.006	.008	.010
AB_SUM	.003	.003	.010	.004
PU_SUM	.008	.005	.002	...
PR_SUM	.004	.002	...	...
KB_SUM	.003	...	...	...

Appendix H – Testing Outliers

Observations farthest from the centroid (Mahalanobis distance) (Group number 1)

Observation number	Mahalanobis d-squared	p1	p2
20	22.726	.001	.212
85	19.230	.004	.267
42	18.477	.005	.158
239	18.209	.006	.068
15	18.008	.006	.026
194	17.486	.008	.017
83	17.463	.008	.005
175	17.400	.008	.001
261	17.293	.008	.000
106	17.024	.009	.000
77	16.829	.010	.000
64	16.745	.010	.000
209	16.656	.011	.000
264	16.398	.012	.000
40	16.383	.012	.000
232	15.960	.014	.000
220	15.858	.015	.000
171	15.326	.018	.000
244	15.155	.019	.000
82	14.936	.021	.000
51	14.690	.023	.000
207	14.577	.024	.000
11	14.232	.027	.000
16	13.920	.031	.000
56	13.446	.036	.000
166	13.381	.037	.000
26	12.548	.051	.001
29	12.536	.051	.000
221	12.402	.054	.000
238	12.117	.059	.001
237	12.082	.060	.000
201	12.043	.061	.000
203	11.823	.066	.000
141	11.790	.067	.000
228	11.761	.068	.000
47	11.663	.070	.000
172	11.555	.073	.000
225	11.475	.075	.000
36	11.323	.079	.000
55	10.833	.094	.002
248	10.826	.094	.001
17	10.361	.110	.011
262	10.333	.111	.008
263	10.333	.111	.005

227	10.313	.112	.003
117	10.164	.118	.005
105	10.071	.122	.006
10	9.968	.126	.007
37	9.762	.135	.015
243	9.722	.137	.012
176	9.695	.138	.009
72	9.526	.146	.017
164	9.459	.149	.017
240	9.285	.158	.030
218	9.095	.168	.058
14	9.030	.172	.059
2	8.994	.174	.052
32	8.939	.177	.050
249	8.867	.181	.053
34	8.832	.183	.047
43	8.693	.192	.071
53	8.692	.192	.053
177	8.662	.193	.046
234	8.620	.196	.043
208	8.383	.211	.108
142	8.313	.216	.117
93	8.167	.226	.175
213	8.165	.226	.143
180	8.141	.228	.126
206	8.076	.233	.134
45	7.994	.239	.155
138	7.946	.242	.154
91	7.941	.242	.127
217	7.882	.247	.133
229	7.879	.247	.107
173	7.773	.255	.143
12	7.575	.271	.268
135	7.529	.275	.270
156	7.165	.306	.645
101	7.154	.307	.608
9	7.115	.310	.603
265	6.770	.343	.895
266	6.764	.343	.873
222	6.687	.351	.897
100	6.626	.357	.910
191	6.592	.360	.907
18	6.571	.362	.897
223	6.569	.363	.873
158	6.407	.379	.942
112	6.405	.379	.926
22	6.351	.385	.934
250	6.331	.387	.927
97	6.286	.392	.931

		6.281	.392	.915
69		6.279	.393	.895
219		6.226	.398	.906
152		6.202	.401	.899
245		6.197	.401	.878
98		6.163	.405	.877
198		6.142	.408	.867

Appendix I – Model Fit Indices (output AMOS)

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	21	7,055	7	,423	1,008
Saturated model	28	,000	0		
Independence model	7	963,391	21	,000	45,876

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	,051	,991	,962	,248
Saturated model	,000	1,000		
Independence model	1,139	,352	,136	,264

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	,993	,978	1,000	1,000	1,000
Saturated model	1,000		1,000		1,000
Independence model	,000	,000	,000	,000	,000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	,333	,331	,333
Saturated model	,000	,000	,000
Independence model	1,000	,000	,000

NCP

Model	NCP	LO 90	HI 90
Default model	,055	,000	10,668
Saturated model	,000	,000	,000
Independence model	942,391	844,499	1047,676

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	,034	,000	,000	,052
Saturated model	,000	,000	,000	,000
Independence model	4,654	4,553	4,080	5,061

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	,006	,000	,086	,722
Independence model	,466	,441	,491	,000

AIC

Model	AIC	BCC	BIC	CAIC
Default model	49,055	50,743	119,143	140,143
Saturated model	56,000	58,251	149,451	177,451
Independence model	977,391	977,953	1000,753	1007,753

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	,237	,237	,288	,245
Saturated model	,271	,271	,271	,281
Independence model	4,722	4,249	5,230	4,724

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	413	543
Independence model	8	9