Impact of Behavioural and Social Factors on the Intention to Adopt Electric Vehicles: An Empirical Investigation

Thesis

Submitted in partial fulfillment of requirements for the degree of

DOCTOR OF PHILOSOPHY

by

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DECLARATION

I hereby *declare* that the research thesis entitled "**Impact of Behavioural and Social Factors on the Intention to Adopt Electric Vehicles: An Empirical Investigation**" which is being submitted to the **National Institute of Technology Karnataka, Surathkal** in partial fulfillment of the requirements for the award of the Degree of **Doctor of Philosophy** in Management is a *bonafide report of the research work carried out by me*. The material contained in this research thesis has not been submitted to any University or Institution for the award of any degree.

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CERTIFICATE

This is to *certify* that the research thesis entitled "**Impact of Behavioural and Social Factors on the Intention to Adopt Electric Vehicles: An Empirical Investigation**" submitted by **Mr. Ansab K V** (Register Number: 177049SM001) as the record of the research work carried out by him, is *accepted as the research thesis submission* in partial fulfilment of the requirements for the award of degree of Doctor of Philosophy.

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Dedicated

to

God Almighty

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ABSTRACT

India is the 3rd largest greenhouse gas emitter and is responsible for 6.9 per cent of global greenhouse emissions. The increase in greenhouse gases is leading to air pollution and climate change. As many as 14 of the world’s top 20 most-polluted cities are in India. Transport sector is one of the major sources of global greenhouse gases emissions, and emissions from conventional petrol/diesel vehicles are making a negative impact on the environment. Thus, it is highly recommended to replace these pollution-causing conventional vehicles with greener eco-friendly vehicles. Electric Vehicles (EVs) are considered to be one of the most promising environment-friendly innovations against pollution and energy demand from the transport sector. Despite strong promotion efforts by government and companies, EVs have a very less market share in India and were only 1.3% of vehicles sold in India during 2020-21. However, studies on EVs are conducted more in developed countries compared to developing countries and more studies are required to enhance EV adoption in developing countries such as India. Specifically, previous researchers have pointed out that there is a dearth of studies on consumer adoption of electric cars. In a practical context, the growth of EV industry in India is led by electric two-wheelers (E2W), and the sales of electric four-wheelers (E4W) have been relatively stagnant. Thus, this study specifically focuses on electric cars as a product category from the electric vehicle industry and aims to analyse various factors influencing consumers’ adoption of EVs in Indian context. The present study utilised an extended Theory of Planned Behaviour (TPB) model to assess the influence of various social and behavioural factors on EV adoption intention among Indian consumers. The study followed a quantitative research method that employed a self-administered survey questionnaire. The target population for the study was individuals with driving license and responses were collected from 738 participants through non-probability purposive sampling. The current research followed Structural Equation Modelling (SEM) using Analysis of Moments Structures (AMOS) to analyse the relationship between adoption intention and its predictors. Willingness to pay premium was found to be the strongest predictor of adoption intention. Among the elements of Theory of Planned Behaviour (TPB) model, attitude exhibited a significant influence on the adoption intention. Among the perceived risk dimensions, Psycho-social risk was found to have a significant negative effect whereas other dimensions did not influence the adoption intention of consumers. Financial incentives did not significantly influence the adoption intention of consumers towards EVs. Along with a direct effect on Attitude, Collectivism and Long-term orientation were also found to have an indirect effect on consumer adoption intention through attitude. The insights from this study would help policymakers, government agencies, and marketers formulate better policies and marketing strategies to increase consumer adoption of electric vehicles in India.

Keywords: electric vehicles, theory of planned behaviour, perceived risk dimensions, cultural dimensions, willingness to pay premium, government financial incentives, consumer behaviour, structural equation modelling.

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List of Abbreviations

Abbreviation	Full Form
BEV	Battery Electric vehicle
EVs	Electric Vehicles
TPB	Theory of Planned Behaviour
ATT	Attitude towards Electric Vehicles
SN	Subjective Norm
PBC	Perceived Behavioural Control
PER	Performance Risk
FIR	Financial Risk
PYR	Physical Risk
PSR	Psycho-Social Risk
COL	Collectivism
LTO	Long-Term Orientation
FIN	Financial Incentives
WPP	Willingness to Pay Premium

CHAPTER 1

INTRODUCTION

According to UN India (2021), India is the 3rd largest greenhouse gas emitter and is responsible for 6.9 per cent of global greenhouse emissions. The increase in greenhouse gases is leading to air pollution and climate change. Considering this scenario, United Nations Sustainable Development Goal 13 (UN-SDG 13) calls for immediate action in reducing greenhouse gas emissions and combating climate change (Montiel, Cuervo-Cazurra, Park, Antolín-López, & Husted, 2021; Porter, Tuertscher, & Huysman, 2020). Transport sector is one of the major sources of global greenhouse gases emissions (IEA, 2021) and is causing air pollution in several cities nationwide. According to World Health Organization (WHO) 2018 report, as many as 14 of the world’s top 20 most-polluted cities are in India (PTI, 2018). Tailpipe emission is one of the biggest contributors of environmental pollution and emissions from conventional petrol-diesel vehicles are making a negative impact on the environment. Thus, it is highly recommended to replace these pollution-causing conventional vehicles with greener eco-friendly vehicles. The mass adoption of eco-friendly vehicles is necessary to achieve UN-SDG 13 and reduce air pollution.

Electric Vehicles (EVs) are considered to be one of the most promising environment-friendly innovations against pollution and energy demand from the transport sector (Wang, Wang, Li, Wang, & Liang, 2018). In the current time, electric vehicles are slowly advancing as a state-of-art technology in the automotive business. Electric Vehicles are promoted as a viable near-term vehicle technology that can help in the reduction of greenhouse gas emissions and the dependence on fossil fuels (Egbue & Long, 2012).

Plug-in Electric Vehicles or Battery Electric vehicles are defined as “the vehicles that derive motive power exclusively from on-board electrical battery packs that can be charged with a plug through an electric outlet” (Egbue & Long, 2012). The major difference of Electric Vehicles (EVs) from conventional vehicles is the type of energy source in them. Conventional vehicles depend on petroleum fossil fuels while Electric Vehicles depend on Electric energy for their functioning.

There is another category of electric vehicles namely Hybrid Electric Vehicles, in which both electricity and conventional petroleum fuels could be used simultaneously. According to Rezvani, Jansson and Bodin (2015), these hybrid electric vehicles can be considered as more fuel-efficient vehicles that do not require any significantly different behaviour from ordinary vehicles. Thus, the present study have focused on adoption of Plug-in Electric Vehicles (Electric vehicles that run exclusively on electricity) which requires behavioural, social and technological changes driven by consumers, companies and government.

According to Singh, Singh, and Vaibhav (2020) and Nie, Wang, Guo and Shen (2018), studies on EVs are conducted more in developed countries compared to developing countries and more studies are required on EV adoption in developing countries such as India. Moreover, despite strong promotion efforts by government, EVs have very less market share in India and was only 1.3% of vehicles sold in India during 2020-21 (Techarc, 2021). Thus, there is a need to study consumer adoption of EVs in Indian context to enhance the consumer acceptance of EVs.

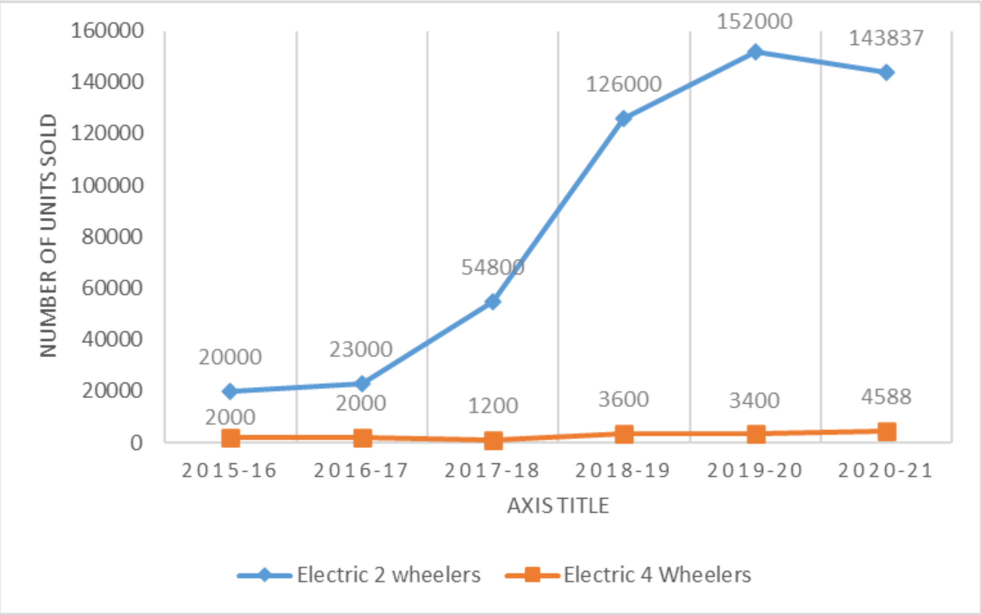


Figure 1.1 Annual EV sales trend in India

Source: Author's own

Researchers have pointed out that there is a dearth of studies on consumer adoption of electric cars (Barbarossa, Beckmann, De Pelsmacker, Moons, & Gwozdz, 2015; Jansson, Marell, & Nordlund, 2010; Mcleay, Yoganathan, Osburg, & Pandit, 2018; Moons & De Pelsmacker, 2012). In a practical context, the growth of EV industry in India is led by electric two-wheelers (E2W), and the sales of electric four-wheelers (E4W) have been relatively stagnant as shown in Figure 1.1 (Society of Manufacturers of Electric Vehicles, 2021). Considering the fact that India is the fourth-largest automobile market (Singh, Singh, & Vaibhav, 2021), this relatively small sales of E4W and their slow market growth is intriguing. Considering electric cars as an innovative product, identifying the motivations and barriers of its acceptance among consumers is really important for the successful introduction of electric cars in the market (Moons & De Pelsmacker, 2012, 2015). Thus, this study specifically focused on electric cars as a product category from the electric vehicle industry in the current study. The terms Electric Vehicles (EVs) and electric cars will be used interchangeably in this report.

Previous researchers have clearly pointed out the lack of enough literature on the pro-environmental behaviour of consumers in developing countries (Ramayah, Lee, & Mohamad, 2010). Green marketing is still in an early phase in India and there is only limited literature on green consumption behaviour in the Indian context (Sreen, Purbey, & Sadarangani, 2018). According to Sreen et al. (2018), Indian consumers are conscious about the deterioration of the environment and feel guilty about their negative effect on the environment. Even though environmental concern is well shown by them, green consumption is not prevalent among Indian consumers. Thus, similar to other green products, EVs are also not widely used by consumers despite all the environmental, economic and social benefits. Since EVs are basically green products, studies on EVs would incidentally be contributing to the limited literature on green consumption in the Indian context.

According to Technology innovation diffusion theory, customers will show reluctance to adopt innovative technologies, especially during its infancy, due to the unfamiliarity, uncertainty and high price associated with such technologically innovative products (Rogers, 2003). It is really important to assess factors that encourage and hinder the acceptance of EVs among consumers for its successful introduction in the market (Moons & De Pelsmacker, 2015). Even though India is the fourth largest automobile market in the world, there are very few studies done on Indian consumers' adoption of electric vehicles. In the present study, Theory of Planned Behaviour (TPB) is used and extended to study the influence of various factors on EV adoption among Indian consumers.

1.1 Literature Review

1.1.1 Theory of Planned Behaviour

The Theory of Planned Behaviour (TPB) was put forward by Ajzen in 1985. In the TPB framework, three constructs namely Attitude, Subjective norm, and Perceived Behavioural Control (PBC) predict an individual's behavioural intention which in turn influence the behaviour. The Theory of Planned Behaviour (TPB) is a model that is extensively utilised in transportation research domain to predict usage intentions. These include studies on speeding intentions (Cristea, Paran, & Delhomme, 2013; Horvath, Lewis, & Watson, 2012), travel mode choices (Hsiao & Yang, 2010) and seat belt usage (Okamura, Fujita, Kihira, Kosuge, & Mitsui, 2012). The current study considered TPB model as the underlying model and extended the TPB model to propose a theoretical framework to predict the adoption intention of EVs in India.

Behavioural intentions could act as a proxy and could contribute towards the prediction of actual technology acceptance (Bamberg, Ajzen, & Schmidt, 2003; Heath & Gifford, 2002). Eco-friendly vehicles, such as Electric Vehicles (EVs), are gaining remarkable approval among consumers across the globe (Adnan, Nordin, Rahman, Vasant, & Noor, 2017). However, in countries such as India where it is relatively a new product, the current number of EVs plying on the road is still low. Hence, it is not feasible to explore their actual adoption at the present time. Therefore, the current study have examined the consumers' adoption intention towards EVs similar to the previous studies done by Sang & Bekhet (2015) and Wang, Li, & Zhao (2017).

1.1.1.1 Attitude towards Electric Vehicles

Attitude is defined as "a psychological path that determines favour or disfavour of an individual towards a specific object". Attitude toward behaviour refers to "the degree to which a person has a favourable or unfavourable evaluation or appraisal of the behaviour in the question" (Ajzen, 1991). An individual would have positive attitude towards a behaviour when its outcomes are evaluated positively (Ajzen, 1991; Han & Kim, 2010). More positive the attitude toward a behaviour, the more will be the chances that an individual would engage in the behaviour. Building positive attitude towards green products would help in increasing consumers' intention towards them and thereby contributes towards a sustainable future for the nation as green products are more environment-friendly.

Previous researchers claim that positive attitude towards a particular behaviour will lead to higher probability of an individual performing that behaviour (Ajzen, 1991). Ramayah, Rouibah, Gopi, & Rangel (2009) emphasised that attitudinal variables have an important role in stimulating the acceptance of innovation and technology. Previous research have supported the positive relationship between attitude and purchase intentions (Bredahl, 2001). According to Paul, Modi, and Patel (2016), attitude have a significant positive impact on consumers' intention to purchase green products. Attitude was found to positively influence consumer's intention to adopt EVs in China (Wang, Wang, Li, Wang, & Liang, 2018). Asadi et al. (2021) supports the positive impact of attitude on consumers' adoption intention by conducting a study on EVs in Malaysian context. Also, attitude have a significant positive association with consumers' EV purchase intention in Beijing (Huang & Ge, 2019). Similarly, Shalender and Sharma (2021) found that attitude towards EVs have a significant positive relationship with consumers' intention to adopt them.

1.1.1.2 Subjective Norm

Subjective norm is defined as 'perceived social pressure to perform or not perform the behaviour' (Ajzen, 1991). In other words, subjective norms are the perceived social pressure an individual faces when deciding whether to behave in a certain way (H. S. Park, 2000). Subjective norm is "the extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology" (Venkatesh, Morris, Davis, & Davis, 2003). An individual is more or less likely to perform a behaviour when he/she feels that the significant others approve/disapprove an action (Conner & Armitage, 1998). Subjective norm is similar to "Social Influence (SI)" in various other technology acceptance theories (Thakur & Srivastava, 2014).

Previous studies have revealed that social externalities, such as subjective norms, social influence, and peer pressure, have an impact on purchasing decisions of consumers (Mohiuddin, Al Mamun, Syed, Masud, & Su, 2018). Subjective norm positively influenced consumers' intention to purchase green housing (L. Zhang, Chen, Wu, Zhang, & Song, 2018). Subjective norm was found to have positive effect on consumers' intention to purchase remanufactured products (Khor & Hazen, 2017). EV acceptance might rely more on perceived social factors once the barriers are resolved (Franke, Schmalfuß, & Rauh, 2018). Subjective norms have a significant impact on Indian consumers' intention to adopt electric vehicles (Shalender & Sharma, 2021). Asadi et al. (2021) found that subjective norms could positively influence consumer's adoption intention towards EVs.

1.1.1.3 Perceived Behavioural Control

According to Ajzen (1991), Perceived Behavioural Control (PBC) refers to "people's perception of the ease or difficulty of performing the behaviour of interest". In the Theory of Planned Behaviour model, PBC is the last determinant of intention. Individuals having a stronger degree of control over themselves would show higher behavioural intention (Ajzen, 1991). PBC could also be described as the perception of an individual regarding the availability of all opportunities and means to engage in a particular behaviour (Conner & Armitage, 1998).

According to the TPB, perceived behavioural control (PBC), along with other elements of the model, could be utilised to predict both intention and actual behaviour (Ajzen, 1991). PBC could have a positive impact on consumers' willingness to pay for eco-friendly products (Al Mamun, Ali Fazal, Ahmad, Yaacob, & Mohamad, 2018). PBC was found to have a significant positive effect on consumers' intention to purchase energy-efficient household appliances (Tan, Ooi, & Goh, 2017). Paul, Modi, and Patel (2016) found that PBC could significantly influence purchase intention towards green products among Indian consumers. The findings of Yadav and Pathak (2017) also showed a positive significant impact of PBC on green product purchase intention in India. A study by Mohiuddin et al. (2018) revealed that PBC is significantly associated with consumers' intention to purchase green vehicles. Similarly, Huang and Ge (2019) found that PBC could significantly influence consumer's EV purchase intention in Beijing. In the Indian context, PBC related to

EVs was found to have a significant positive effect on consumers' adoption intention towards EVs (Shalender & Sharma, 2021).

1.1.2 Perceived Risk

Perceived risk is a psychological construct that is gaining increased attention in social psychology research. According to Dunn, Murphy and Skelly (1986), perceived risk could be defined as "the expected negative utility that consumers associate with the purchase of a particular product or service". Several studies were done on determining the various dimensions and types of risks involved in consumer purchase decisions and behaviour. According to Jacoby and Kaplan (1972) and Kaplan, Szybillo, & Jacoby (1974), the various types of risks involved during product purchase are Performance risk, Financial risk, Physical risk, Psychological risk, and Social risk. Jacoby & Kaplan (1972) determined these five types of risks through a study done across 12 different products and found that these five risk dimensions explained, on average, 74 per cent of the variance in the overall perceived risk associated with product purchase. Interestingly, these five risk varieties can also be inferred from Bauer's original work (Jacoby & Kaplan, 1972). It is worth noting that Raymond Bauer was the first to formally propose the concept of perceived risk in consumer behaviour studies in 1960 (Taylor, 1974). The various facets or dimensions of perceived risk considered in the current study are as follows:

1.1.2.1 Performance Risk

Performance risk may be defined as "the possibility that a procured product would not work as properly as it is supposed to" (Jacoby & Kaplan, 1972). Performance risk refers to "the probability that a product purchased results in failure to function as expected" (Featherman & Pavlou, 2003). This risk is also termed as Functional risk by previous authors (Beneke, Greene, Lok, & Mallett, 2012; Yang, Pang, Liu, Yen, & Michael Tarn, 2015) considering that it is related to the functionality or usefulness of the product (Lim, 2003). During many purchase decision scenarios, consumers might not be able to collect all the relevant information regarding the quality of a product. Thus, performance risk could also arise from such inappropriate product selection of consumers (Forsythe & Shi, 2003).

Performance risk was found to be a significant risk dimension in various studies carried out on the risk perception of consumers (Jacoby & Kaplan, 1972; Forsythe & Shi, 2003; Lee, 2009; Beneke et al., 2012; Yang et al., 2015; Akturan & Tezcan, 2012). Compared to conventional vehicles, EVs have performance differences as they are innovative green vehicles (Jensen, Cherchi, & Mabit, 2013). Thus, there are chances for the consumers to be skeptical about its performance and may thus perceive higher performance risk related to purchase of EVs.

1.1.2.2 Financial Risk

Financial risk refers to the "probability that a purchase results in loss of money or other resources" (Chen & He, 2003). Sometimes it is defined as "the consumers' concern for the monetary value of products, or the concern about how much money would get wasted if the product does not perform as per consumers' expectations" (Mitchell, 1998). Financial risk was revealed to be a significant risk dimension across product categories in various studies on perceived risk (Forsythe & Shi, 2003; Jacoby & Kaplan, 1972; Lee, 2009; Yang et al., 2015; Stone & Grønhaug, 1993).

Financial risk relates to the potential negative financial outcomes which are associated with new product adoption (Stone & Grønhaug, 1993). The owners of hybrid cars (particular plug-in vehicles) may gain financial benefits from policy-related remunerations and lower fuel costs (Gallagher & Muehlegger, 2011; Ozaki & Sevastyanova, 2011). However, users face expensive initial purchase prices and high maintenance costs for batteries, which may impede adoption. According to Mcleay et al. (2018), the role that financial risk can play in influencing purchasing intentions for high involvement, eco-friendly vehicles such as cars has not been explored.

1.1.2.3 Physical Risk

Physical risk may be defined as "probability that the use or consumption of a product may be harmful or injurious to health" (Jacoby & Kaplan, 1972; Mitchell, 1998). Previous studies on physical risk has found that it is a significant facet of perceived risk (Hirunyawipada & Paswan, 2006; Jacoby & Kaplan, 1972). As an evolving technology product, there are chances for existence of some safety issues in BEVs (Egbue & Long, 2012). Also, consumers may have concerns regarding contingency that may arise, such as bursting of batteries and other physical damages etc. Thus, in the context of Electric Vehicles, Physical risk could be considered as a potential loss caused due to the safety-related aspects of EVs (Egbue & Long, 2012). EVs are innovative green products with which consumers have varying familiarity and knowledge. There is a need to understand how the perceived physical risk associated with EVs may influence its adoption among consumers.

1.1.2.4 Psychosocial Risk

Dholakia (2001) defined psychological risk as "the nervousness arising from the anticipated post-purchase emotions such as frustration, disappointment, worry, and regret". Psychological risk can also be defined as "anxiety and/or uncomfortable feelings arising from anticipated post-behavioural emotions such as worry and tension" (Hirunyawipada & Paswan, 2006). Prior studies have already explored the hedonic attributes (i.e. positive emotions) associated with driving hybrid electric vehicles (Moons & De Pelsmacker, 2012; Schuitema, Anable, Skippon, & Kinnear, 2013). However, the negative influence of consumers' emotions on electric vehicle adoption have not been fully explored (Adnan et al., 2017). As emotions can be a strong determinant of consumer behaviour in high-involvement situations (Moons & De Pelsmacker, 2012), psychological risk is likely to influence the adoption of eco-friendly vehicles such as cars (Barbarossa, Beckmann, De Pelsmacker, Moons, & Gwozdz, 2015). Social risk is defined as the "possibility that the purchase of an unfamiliar product by a person may affect the manner in which relevant others (friends, neighbours etc.) think of the former" (Jacoby & Kaplan, 1972). It can also be defined as the "potential loss of a person's social position within the social group, in view of purchasing a new product" (Featherman & Pavlou, 2003). Social risk refers to the negative consequences associated with unfavourable opinions of significant other people on account of the purchase and use of a product (Dholakia, 2001). Social risk is an important risk facet in the sense that purchase decisions are influenced by others in the society (Beneke et al., 2012), and that the shopping behaviour of a particular customer may not be accepted by others (Lim, 2003). Sometimes when the purchased product does not work as expected, consumers may feel foolish or others might make them feel so (Roselius, 1971). Social risk was identified to be significant in the previous research conducted on consumer risk perceptions (Akturan & Tezcan, 2012; Hirunyawipada & Paswan, 2006; Jacoby & Kaplan, 1972). The seminal study by Jacoby and Kaplan (1972) and Peter and Tarpey (1975) stated that psychological risk and social risk could be integrated into “Psychosocial risk”. In line with this, previous studies have supported combining psychological risk and social risk into “psychosocial risk” and found psychosocial risk to be important in the consumer behaviour context (Korgaonkar & Karson, 2007; Liljander, Polsa, & van Riel, 2009; Vincent-Wayne Mitchell & Harris, 2005; Ortega-Egea & García-de-Frutos, 2021; Pueschel, Chamaret, & Parguel, 2017; Shan, Jiang, & Cui, 2021; Voyer & Ranaweera, 2015). The current study aims to analyse the effect of psychosocial risk on adoption intention towards EVs among Indian consumers.

1.1.3 Culture

According to Hofstede (1980), “Culture refers to the collective mental programming that people have in common; the programming that is different from that of other groups, tribes, regions, minorities or majorities, or nations”. Hofstede's cultural dimensions are widely used to research consumer purchase intention across various cultures (Sreen et al., 2018). Hofstede's cultural dimensions include Collectivism, Long-term orientation, Uncertainty avoidance, Masculinity and Power distance. Amongst these dimensions, Collectivism and long-term orientation (LTO) are the most widely accepted dimensions for predicting environment-friendly purchase intention (Cho, Thyroff, Rapert, Park, & Lee, 2013; Leonidou, Leonidou, & Kvasova, 2010).

There are numerous studies that explored the influence of Hofstede’s cultural dimensions in the adoption of new technology and products. van Everdingen and Waarts (2003) studied the influence of national level Hofstede’s cultural dimensions on the adoption rate of Enterprise Resource Planning (ERP) software across ten European countries and clearly mentioned the influence of culture in the adoption of ERP. Erumban and de Jong (2006) have studied the influence of national level Hofstede dimension on the adoption rate of ICTs across 42 countries. They stated that the influence of culture in the adoption is not just applicable for ERPs or ICTs. But in general, culture can influence the adoption of any new technology in the market.

As mentioned earlier, Collectivism and long-term orientation (LTO) are the most widely accepted dimensions for predicting environment-friendly purchase intention (Cho et al., 2013; Leonidou et al., 2010). Thus, the present study aims to study how collectivism and long-term orientations are influencing the consumer adoption intention of EVs.

1.1.3.1 Collectivism

The dimension of collectivism is often explained along with its opposite, Individualism. According to Hofstede (1980), “Individualism implies a loosely knit social framework in which people are supposed to take care of themselves and of their immediate families only, while collectivism is characterized by a tight social framework in which people distinguish between in-groups and out-groups; they expect their in-group (relatives, clan, organizations) to look after them, and in exchange for that they feel they owe absolute loyalty to it”.

Previous studies on the effect of collectivism on consumer purchase decisions have resulted in contradictory results. Nguyen, Lobo and Greenland (2017) found that collectivist societies show a strong willingness to purchase environment-friendly products in emerging markets. In a study conducted for the adoption intention of online personalised products, individualism is found as the most influencing dimension among the four Hofstede cultural dimensions (Moon, Chadee, & Tikoo, 2008). However, some other studies suggest that collectivism does not play much role in influencing the purchase intention of products which have not reached masses (Varshneya, Pandey, & Das, 2017). Electric vehicles are currently in their nascent stage in India. So, it really important to analyse the role of collectivism on the consumer adoption of Electric Vehicles.

1.1.3.2 Long-Term Orientation

Long-Term Orientation (LTO) “stands for the fostering of virtues oriented toward future rewards, in particular, perseverance and thrift” (Hofstede, 2001). In other words, it could explain how much a society values long-term standing over short-term values and traditions. It was added later with the initial four cultural dimensions proposed by Hofstede and is considered to be important and relevant, especially in Asian countries (Chekima, Chekima, Syed Khalid Wafa, Igau, & Sondoh, 2016).

According to Bearden, Money and Nevins (2006), LTO is a salient dimension among Hofstede’s dimensions and influence the consumers’ decision-making process.

LTO could have a significant positive influence on consumers' environmental attitudes (Nguyen et al., 2017). Gul (2013) found that the Long-term orientation of consumer positively influences the Environment Conscious Consumer Behaviour (ECCB). A study by Sreen et al. (2018) in Indian context revealed that LTO have an indirect effect on consumers' green purchase intention. Similarly, LTO was found to have a significant effect on green purchase intention of consumers (Chekima et al., 2016). LTO is an important cultural dimension in green consumer behaviour that have an impact on consumers' evaluation of electric vehicles (Qian & Yin, 2017) and hence could influence consumers' decision making related to EVs. Thus, the current study analyses how LTO would influence consumer's adoption intention towards EVs.

1.1.4 Willingness to Pay Premium

Price is one of the most important elements in marketing mix concept. Indian consumers are price sensitive in nature and price is still a factor that influences them (Manaktola & Jauhari, 2007). Regarding the price, green products usually have a higher price due to the high cost incurred in various processes (manufacturing, certification etc.) associated with green products. EVs are priced at least 30% higher than conventional vehicles (Singh et al., 2021). For instance, the petrol variant of Tata Tigor comes with a starting ex-showroom price of around 6 lakhs INR compared to 12 lakhs INR for its electric variant. High purchase price of EVs is a major barrier against the purchase of EVs among Indian consumers (Shalender & Yadav, 2018)

Furthermore, consumers who have previously experienced eco-friendly products would be willing to pay more for them (Shen, 2012). As electric vehicles have very less market share and relatively very few dealerships are selling them, consumers might not have enough opportunity to experience and use them. So as a green product, Willingness to Pay Premium (WPP) for electric vehicles would be an important factor influencing its adoption by consumers, especially during its introduction stage. In the developing country context, Yadav and Pathak (2017) have supported the inclusion of additional construct, willingness to pay premium in their study using Theory of Planned Behaviour (TPB). The inclusion of WPP has improved the predictive power of the theoretical framework for determining the consumers' green purchase intention and behaviour. But, previous studies have stated that the influence of willingness to pay premium may vary from one product category to other (Shen, 2012; Yadav & Pathak, 2017). So, there is a clear need to analyse how the consumer "willingness to pay premium" will influence the product category of electric vehicles and their adoption.

1.1.5 Financial Incentives

Governments across the world have initiated policies for reducing CO_2 emissions by stimulating the production, introduction and adoption of EVs (Brady & O'Mahony, 2011). According to Zhu et al. (2019), reducing the cost of electric vehicles is the first step to be taken by governments and stakeholders to increase its market penetration. In 2013, The National Electric Mobility Mission Plan 2020 (NEMMP 2020) by Indian government considered financial incentives as a major method to create demand for electric vehicles in the country. If not implemented effectively, financial incentives could be a burden to the government without any long-term impact on the user adoption of electric vehicles. In other words, it would reduce to become just redistribution of wealth and benefits from government without much contribution to mass EV adoption (Coffman, Bernstein, & Wee, 2017).

As innovative fuel-efficient vehicles, EVs have higher purchase price compared to conventional vehicles (Coad, de Haan, & Woersdorfer, 2009; Lieven, Mühlmeier, Henkel, & Waller, 2011). This high initial purchase price is a crucial barrier against the mass acceptance of EVs (Egbue & Long, 2012). To lower the purchase price, many financial incentives, such as direct subsidies have been provided. Under NEMMP 2020, Faster Adoption and Manufacturing of (Hybrid &) Electric Vehicles in India (FAME India Scheme) was introduced with a notion that financial incentives would help in breaking the barrier associated with the higher initial price associated with the purchase of EVs. The financial incentives provided by the central government under FAME India scheme is expected to promote and increase the demand for EVs among consumers (Government of India, 2019).

As battery cost is a major reason for the higher price of EVs, the FAME incentives are provided based on the capacity of battery (indicated in kiloWatts-hour or kWh) used in such vehicles. The E4W will be provided with INR 10,000 per kWh of battery used, and such incentives are capped at 20% of the cost of vehicles. These incentives are provided to consumers as reduced up-front purchase price to consumers at the time of purchase and will be reimbursed to the manufacturer by the central government. Similarly, the Ministry of Finance has announced a lower GST of 5% for all EVs and income tax benefits (up to INR 1,50,000) could be availed by buyers taking loans to purchase EVs (Government of India, 2020). Over and above the benefits provided by central governments, various state governments are also providing purchase incentives along with other financial benefits such as registration fee waiver, road tax waiver etc.

However, the current market penetration of EVs is relatively low in spite of many governments implementing strong promotion policies. The low market share of EVs underlines the need for further investigation into the impact of government financial incentives on consumers' EV adoption intention.

1.1.6 Adoption Intention

Behavioural intention is defined as "the willingness and intention of an individual to perform certain behaviour" (Ling Keong, Ramayah, Kurnia, & May Chiun, 2012). According to Venkatesh, Morris, Davis and Davis (2003), behavioural intention can be used to predict desired behaviour or actual use of a technology. The TPB suggests that behavioural intention is the most influential predictor of behaviour.

Considering the crucial role played by consumers in innovation diffusion, consumer adoption of new products is a topic of great interest among consumer behaviour and marketing researchers (Im, Bayus, & Mason, 2003). Attitude does not directly influence the purchase behaviour. Intentions act as the first stage before green attitude can actually translate into green purchase behaviour (Groening, Sarkis, & Zhu, 2018).

Intention could be considered as an immediate predictor of actual behaviour. An appropriate measurement of intention would help in nearly accurate determination of behaviour. For instance, previous researchers such as Heath and Gifford (2002) indicated that intention is a proxy variable for adoption behaviour.

In Battery Electric Vehicle acceptance (BEV) research, BEV adoption intention is often the focus of research considering the comparatively low market share of BEVs and the resulting low possibility of investigating actual behaviour (Franke et al., 2018; Rezvani et al., 2015). Previous studies support that measuring intention will give acceptable indication of consumer behaviour (Thakur & Srivastava, 2014). Thus as suggested by previous researchers, adoption intention was considered in the present study than actual adoption behaviour (Sang & Bekhet, 2015; S. Wang et al., 2017).

1.2 Gap Areas

Although there are studies on general green products, research on specific product categories, such as green vehicles, are relatively less in the literature (Mohiuddin et al., 2018; Zhang & Dong, 2020). Among green vehicles, the present study focuses on the consumer adoption of electric vehicles. The review of literature revealed that it is essential to explore and understand the various factors influencing consumers' intention to adopt electric vehicles (Wang et al., 2018).

According to Moons and De Pelsmacker (2012) and Jansson et al. (2010), there is a dearth of studies that analysed consumer behaviour regarding high-involvement green products, such as electric cars. Literature review revealed that there are very few studies done on consumer adoption intention towards electric cars (Barbarossa, Beckmann, De Pelsmacker, Moons, & Gwozdz, 2015; Jansson, Marell, & Nordlund, 2010; Mcleay, Yoganathan, Osburg, & Pandit, 2018; Moons & De Pelsmacker, 2012). Moreover, there is relatively less research done on electric vehicles in developing countries compared to developed countries (Nie, Wang, Guo, & Shen, 2018; Singh et al., 2020). Majority of the studies were done in the context of developed countries and some developing countries like China, Malaysia where the circumstances, culture and attitudes are entirely different from other developing countries such as India. The current study responds to the above-mentioned gaps by analysing the consumer adoption of electric cars in India, which is the fourth largest automobile market in the world. Specifically, the present study tries to assess the effect of various determinants on the intention to adopt electric cars among consumers in India. From the literature review, the following gap areas have been identified:

- The Perceived risk construct in this study is in line with the previous studies suggesting that barriers of sustainable consumption should also be determined, not just the drivers (Hüttel, Ziesemer, Peyer, & Balderjahn, 2018; McLeay, Yoganathan, Osburg, & Pandit, 2018; Van Doorn & Verhoef, 2015). Park, Lim, and Cho (2018) and Tarei, Chand, and Gupta (2021) proposed that future studies should extend the literature by investigating the potential risks and problems associated with EVs.

  In addition, previous researchers mostly considered perceived risk as a single construct (Jiang & Zhu, 2018). But, it is essential to consider perceived risk as a multi-faceted construct in order to understand the real characteristics of perceived risk and how exactly it influences consumer behaviour (Lee, 2009). Thus, the present study have considered various dimensions of perceived risk and their influence on adoption intention of EVs.

- Consumers from developing countries are mostly assumed to be unwilling to pay extra premium prices for green and eco-friendly products. Therefore, only less research are conducted to study those consumers' willingness-to-pay in non-affluent consumer markets. Previous studies have claimed that it is premature to conclude that the developing country consumers are not ready to make pro-environmental choices in the marketplace (van Kempen, Muradian, Sandóval, & Castañeda, 2009).

  Yadav and Pathak (2017) have measured the influence of Willingness to Pay Premium (WPP) on the purchase intention of green products in general. They stated that consumer behavioural intention vary across various ranges of green products such as energy-saving appliances, organic food, green hotels etc., and hence their findings cannot be generalised across all green product categories. Thus, there is a need to analyse how willingness to pay premium would influence the adoption intention in specific product categories, such as Electric Vehicles. Considering the dearth of studies on EV adoption in India, the current study aims to determine the influence of willingness to pay premium on consumer adoption intention of Electric Vehicles.

- The perception of consumers regarding current policies associated with environment, fuels, vehicles and specifically EVs could have an impact on their behaviour towards EVs (Lane & Potter, 2007; Sovacool, 2009). In the context of consumer preference of electric vehicles, Liao, Molin, and van Wee (2017) pointed out that there is hardly any consensus on the effectiveness of incentive policies on Electric Vehicles preferences. Rezvani et al. (2015) called for further research on consumers' perception of certain policies related to EVs and its effect on the intention towards EVs. However, majority of the previous research on EV adoption have focused on the attitudinal factors and infrastructure conditions related to EVs, thus ignoring the impact of government policy measures on EV adoption (Yang, Cheng, Li, & Shanyong, 2019). Yang et al. (2019) stated that further studies are required to understand the effect of consumer perception regarding government policies on their intention towards electric vehicles. Furthermore, Arribas-Ibar, Nylund, and Brem (2021) pointed out the need for further empirical research on the effect of financial policies on electric vehicles as a research gap in the literature that needs to be filled. Thus, the present study aims to analyse how the financial incentives by government would influence the adoption intention of EVs among Indian consumers.

- Most of the previous researchers have been considering the National level cultural dimensions proposed by Hofstede while doing their research related to the influence of culture on behavioural intention. But different from previous studies, researchers have started using individual-level measurement of Hofstede's cultural dimensions in their studies. Yoo, Donthu and Lenartowicz (2011) stated that it is erroneous to stereotype an entire country population based on national level measurement of Hofstede's indices. They believe that culture is not inherited by birth, but it changes over time. Globalisation, international travel, internet are all changing people into global citizens with individual beliefs, values and culture.

  Sreen et al. (2018) and Leonidou et al. (2010) have created a path from individual-level cultural values to green purchase intention and behaviour through attitude. Sreen et al. (2018) stated that it is crucial to study the impact of cultural dimensions on green purchase intention, especially for developing countries. Since the focus of their research was on the broad category of green products, Sreen et al. (2018) calls for further research on specific product categories and thus analyse the impact of individual-level cultural values on the subcategories of green products. Thus, the current study aims to examine the mediating role of attitude in the relationship between individual level cultural dimensions and adoption intention of the electric vehicle product category.

1.3 Research Objectives

On the basis of the gaps found in the literature review, the following objectives have been formulated:

1) To examine the influence of the elements of Theory of Planned Behaviour on the adoption intention of electric vehicles among Indian consumers.

2) To assess the influence of Perceived risk facets associated with electric vehicles on the intention to adopt electric vehicles.

3) To examine the influence of willingness to pay premium (WPP) for electric vehicles on the intention to adopt electric vehicles.

4) To assess the influence of financial incentives by government on the intention to adopt electric vehicles.

5) To examine the influence of cultural dimensions (Collectivism and Long-term orientation) on the intention to adopt electric vehicles and to assess the mediating role of attitude in the relationship between the individual level cultural dimensions and intention to adopt electric vehicles.

1.4 Theoretical Background and Hypotheses Development

1.4.1 Theory of Planned Behaviour and Adoption Intention of EVs

According to the TPB, attitude, along with other elements of the model, could predict both intention and actual behaviour (Ajzen, 1991). In the case of eco-friendly innovations, attitude has been found to be a strong determinant of an individual's willingness to adopt them (Jansson et al., 2010). Particularly, previous studies revealed that attitudinal factors have a positive influence on consumers' intentions to acquire eco-friendly vehicles (Wu, Trappey, & Feinberg, 2010). In a survey study to explore consumer's intention towards environment-friendly cars, Klöckner, Nayum, & Mehmetoglu (2013) concluded that those with a positive mindset towards environment have more eagerness to adopt green vehicles. According to Varshneya et al. (2017), green products like EVs are in their introductory stage in emerging economies, such as India. People would not have developed an attitude towards EVs in the current scenario. Thus, there is a need to study how attitude might influence adoption intention of EVs among Indian consumers in the present scenario.

There have been various studies that tried to study the relationship between social influence and adoption intention of new technology as well as green products. For example, studies by Varshneya et al. (2017) and Paul, Modi and Patel (2016) found that social influence is not affecting the adoption intention of environment-friendly products by consumers. However, Sreen et al. (2018) found out that subjective norms have significant relationship with the adoption intention of green products. Similarly, in electric car context, Moons and de Pelsmacker (2012) identified a significant association between subjective norms and electric car usage. Thus, the inconsistent findings in the literature regarding the relationship between SN and adoption intention of new technology calls for further research of the relationship in various contexts as pointed out by Mohiuddin et al. (2018).

In the TPB, Perceived Behavioural Control (PBC) is the final determinant of intention. PBC deals with an individual's beliefs or his/her personality traits such as self-confidence and self-efficacy (Ajzen, 1991). This concept refers to factors that could either obstruct or encourage an individual to undertake a certain behaviour. In the recent scenario, the perceived behavioural control consists of the perception of technology, price, availability or knowledge to use the Plug-in Hybrid Electric Vehicle (PHEV), and capability to perform the adoption behaviour (Adnan, Md Nordin, Hadi Amini, & Langove, 2018). López-Mosquera and Sánchez (2012) stated that the more a consumer has the ability to control various elements, the more behavioural intention will be developed. Mohiuddin et al. (2018) calls for further research on the relationship between PBC and intention. Thus, the following hypotheses were formulated:

H_1: There is a significant positive relationship between attitude and adoption intention of EVs

H_2: There is a significant positive relationship between subjective norms and adoption intention of EVs

H_3: There is a significant positive relationship between perceived behavioural control and adoption intention of EVs

1.4.2 Perceived Risk Facets and Adoption Intention of EVs

Literature review reveals that perceived risk have significant influence on adoption intention of consumers. Perceived risk was found to have significant influence on purchase intention of green remanufactured products by consumers (Y. Wang & Hazen, 2016). Similarly, Perceived risk was found to have a negative influence on the consumers' intention to adopt EVs (Li, Long, Chen, & Geng, 2017; S. Wang et al., 2018). Various facets of perceived risk have already been discussed under the literature review section. From a consumer perspective, various facets of perceived risk associated with product purchase are Performance risk, Financial risk, Physical risk, Psychological risk and Social risk (Jacoby & Kaplan, 1972).

Performance risk was the most predictive of the overall perceived risk for most of the kinds of products in the study done by Jacoby and Kaplan (1972). Kaplan et al. (1974) later cross-validated and confirmed the influence of performance risk through the same study (conducted in 1972) with different subjects. Antioco and Kleijnen (2010) found that performance risk have significant influence on consumers' adoption intention of technological innovations. Similarly, performance risk was found to have a negative significant relationship with consumers' intention to use internet banking (Kesharwani & Tripathy, 2012). A study by Akturan (2020) revealed that performance risk have an impact on consumers' payment behaviour related to high-involvement green products. According to Sang and Bekhet (2015), the performance of eco-friendly vehicles (such as EVs) can play an important role in its acceptance among consumers. Therefore, performance risk could influence consumer adoption of EVs and hence the current study focuses on studying the influence of performance risk on the consumer adoption of EVs.

Electric vehicles are innovative emerging technology products. Financial risk could motivate consumers to acquire more information regarding new high technology products (Hirunyawipada & Paswan, 2006), such as electric vehicles. Previous studies on emerging technologies have found perceived financial risk to be an important and significant dimension among the various perceived risk dimensions (Featherman & Pavlou, 2003; Luo, Li, Zhang, & Shim, 2010). Financial risk have a significant negative impact on consumers' intention to adopt online banking (Lee, 2009). Al Majali (2020) found that financial risk could have a significant negative effect on consumers' attitude towards purchasing electric vehicles. However, some other studies revealed that financial risk does not play a significant role in consumer behaviour context. Akturan and Tezcan (2012) found that perceived financial risk does not have an impact on consumer attitude. Financial risk was not found to affect consumers' behavioural intention related to hotel services (Sun, 2014). Perceived financial risk did not have significant effect on counterfeit luxury consumption of consumers (Pueschel et al., 2017). Financial risk did not influence the purchase intention towards premium grocery private label brands (Beneke et al., 2012). Similarly, previous study on electric vehicles by Jiang (2016) revealed that financial risk have an insignificant effect on the consumer purchase intention towards electric vehicles. The contrasting findings from the previous studies calls for further research on the impact of financial risk on consumer adoption intention of EVs. Thus, the current study hypothesised that financial risk have a negative significant effect of consumers' adoption intention of EVs.

Psychosocial risk plays an important role in influencing the consumer behaviour and their purchase decisions. Higher psychosocial risk is associated with higher involvement by the consumer regarding their purchase decision (Voyer & Ranaweera, 2015). Korgaonkar and Karson (2007) found that consumers prefer products with low psychosocial risk compared to the ones with high psychosocial risk. Psychosocial risk was found to influence the counterfeit luxury consumption of consumers (Pueschel et al., 2017). A study in the product purchase context by Ortega-Egea and García-de-Frutos (2021) revealed that psychosocial risk could be significantly related to consumers' reluctance towards product purchases. Psychosocial risk have a significant effect on the purchase of socially responsible goods (Boivin, Durif, & Roy, 2011). Thus, psychosocial risk was hypothesised to have a significant influence on the adoption intention of EVs.

Physical risk is another risk facet that is important in consumer behaviour context and their purchase decision regarding products. Previous studies found that physical risk did not influence the consumers' purchase intention towards premium grocery private label brands (Beneke et al., 2012) and counterfeit luxury consumption (Pueschel et al., 2017). Electric vehicle is a type of alternative fuel vehicle and Petschnig, Heidenreich and Spieth (2014) found that physical risk does not play a significant role in influencing consumer behaviour related to alternative fuel vehicles. Similarly, Al Majali (2020) found that physical risk did not have significant impact on consumer attitude towards EVs. However, Safety risk was found to have an impact on consumer intention to use transportation services (Tran, 2020). In the context of EVs, the study by Jiang (2016) revealed that physical risk would negatively influence consumer's purchase intention towards EVs. Thus, the contrasting findings from previous studies regarding the impact of physical risk on consumer behaviour necessitates further research on how physical risk influence consumers' EV adoption intention. In the current study, physical risk is hypothesised to have a negative significant influence on consumers' EV adoption intention.

Moreover, as mentioned before in the research gap section, most of the previous studies have considered perceived risk as a single construct. The dimensions of risk are very product specific and can be independent of each other (Laroche, McDougall, Bergeron, & Yang, 2004). In other words, these dimensions can be considered functionally independent on conceptual level. As one risk dimension increases or decreases, it would not influence or affect whether the other risk dimensions are increasing, decreasing or remaining constant (Jacoby & Kaplan, 1972). In fact, the types of risk perceived by consumers could vary according to the characteristics and attributes of a product (Featherman & Pavlou, 2003). Considering EVs as an innovative product, there is a clear need to explore the influence of various facets of perceived risk on the adoption intention of EVs. Thus, hypotheses were formed as follows:

H_4: There is a significant negative relationship between performance risk and adoption intention of EVs.

H_5: There is a significant negative relationship between financial risk and adoption intention of EVs.

H_6: There is a significant negative relationship between physical risk and adoption intention of EVs.

H_7: There is a significant negative relationship between psychosocial risk and adoption intention of EVs.

1.4.3 Willingness to Pay Premium and Adoption Intention of EVs

Price is an important factor influencing the consumer behaviour, especially in developing countries such as India. Previous studies found that the tendency for green consumption of consumers reduces with the increase in the price of green products (Abaidoo, 2010). Willingness to pay premium for eco-friendly products would have a significant impact on consumers' paying behaviour for eco-friendly products (Al Mamun, Ali Fazal, et al., 2018). Similarly, Kang, Stein, Heo, and Lee (2012) supported the idea that willingness to pay premium have an impact on the green purchase intention. Cowan and Kinley (2014) found that willingness to pay more for green apparels have an impact on their purchase intention towards them. Previous studies on consumers' behavioural intention towards green hotels in India revealed the willingness to pay premium to have a significant impact on green behavioural intention (Dwivedi, Pandey, Vashisht, Pandey, & Kumar, 2022; Yadav, Balaji, & Jebarajakirthy, 2019). Similarly, willingness to pay premium could influence the purchase intention of consumers towards eco-friendly packaged products (Prakash & Pathak, 2017). In the context of electric vehicles, Ng, Law and Zhang (2018) found that willingness to pay more is significantly and positively related to consumers' purchase intention towards electric vehicles. Electric vehicle is an innovative green product in India and willingness to pay premium could be hypothesised to have a positive significant effect on the adoption intention of EVs among Indian consumers. Thus, following hypothesis was formulated:

H_8: There is a significant positive relationship between willingness to pay premium and adoption intention of EVs.

1.4.4 Financial Incentives and EV Adoption Intention

Consumer's perception and acceptance of policies are topic of great interest among researchers in consumer behaviour. Previous studies related to the impact of government incentives on EV adoption provided mixed evidence and there is a lack of consensus on its effectiveness among researchers (Coffman et al., 2017). Many study have examined the influence of financial incentives on EV adoption and have found that financial incentives have a positive effect on the intention to adopt EVs. In a study conducted among Malaysian consumers, it was found that government's role is an important predictor of green purchasing behaviour (Sinnappan & Rahman, 2011). Sang and Bekhet (2015) found that government policy interventions, such as subsidized purchase price, positively influence the usage intention of EVs in Malaysia. Suxiu Li, Yingqi Liu and Jingyu Wang (2015) observed that subsidies and tax incentives are indispensable for the development of EVs in their study on factors influencing EV adoption conducted among 14 international cities/regions. Münzel, Plötz, Sprei and Gnann (2019) found that financial incentives would positively influence EV adoption. However, Wang, Tang, and Pan (2019) found that government subsidies are not the reason for huge difference in EV adoption. Similarly, the increased government incentives in China did not get translated to the expected level of boost and market growth for EVs (Nie et al., 2018). Diamond (2009) found a weak relationship between government incentives and adoption of Hybrid electric vehicles among US consumers. Wang et al. (2018) found financial incentives does not have significant influence on consumer adoption intention of electric vehicles. Li et al. (2018) pointed out that the effect of financial incentives is not as powerful as expected. Zhang, Wang, Hao, Fan, & Wei (2013) assessed the impact of government policy on consumers' EV preference and found that performance attributes are the most important indicator compared to financial benefits. Thus, the contradictory findings by the previous researchers bring in the need for further research on the influence of governments' financial incentives on the adoption intention of EVs among Indian consumers. The following hypothesis was formulated:

H_9: There is a significant positive relationship between financial incentives and adoption intention of EVs.

1.4.5 Attitude as a Mediator between Cultural Values and EV Adoption Intention

Studies indicate that even in the age of globalisation, culture can be considered as an important factor influencing the acceptance of a new product (Yeniyurt & Townsend, 2003). Cultural differences affect consumer behaviours, such as attitudes and persuasion, diffusion of new products as well as product and service usage (Moon et al., 2008). It adds a great deal of complexity and perceived uncertainty in the marketing environment and impacts all aspects of marketing (Takada & Jain, 1991).

In the present study, Hofstede's cultural dimensions are considered. Amongst the five dimensions, Collectivism and long-term orientation (LTO) are the most widely accepted dimensions for determining green purchase intention (Leonidou et al., 2010; Sreen et al., 2018). Previous studies revealed a positive relationship between collectivism and environmental attitude (Leonidou et al., 2010; Nguyen et al., 2017). As environmental products are beneficial for the future, individuals with long-term orientation would develop a positive attitude towards such products (Leonidou et al., 2010; Sreen et al., 2018). Among all the TPB elements, attitude was found to have the strongest direct effect on consumers' green purchase intention in Indian context (Paul et al., 2016; Varshneya et al., 2017; Yadav & Pathak, 2016).

Leonidou et al. (2010) established a relationship between cultural factors (collectivism and long-term orientation) with green consumer behaviour through attitude. Sreen et al. (2018) created a path from cultural values to green purchase intention through attitude as mediator. But, their research was focused on the broad product category of green products and Sreen et al. (2018) calls for further research on specific product categories. The present study focuses on the specific product category of electric vehicles. Thus, the study aims to assess the mediating role of attitude between individual-level cultural factors (Collectivism, Long-term orientation) and the intention to adopt electric vehicles. Hence, the following hypotheses were formulated:

H_{10}: There is a significant positive relationship between collectivism and attitude towards EVs

H_{11}: There is a significant positive relationship between long-term orientation and attitude towards EVs

H_{12}: The influence of collectivism on adoption intention of EVs is mediated by the attitude towards EVs

H_{13}: The influence of long-term orientation on adoption intention of EVs is mediated by the attitude towards EVs

Based on the hypotheses formulated, a conceptual model was developed as illustrated in Figure 1.2. The hypothesised relationships that need to be tested is clearly shown in the conceptual model. The positive hypothesised relationships between constructs were indicated with a ‘+’ sign and negative hypothesised relationships between constructs were indicated with a ‘-‘ sign. The proposed conceptual model and the hypothesised relationships were assessed using structural equation modelling in the subsequent chapters.

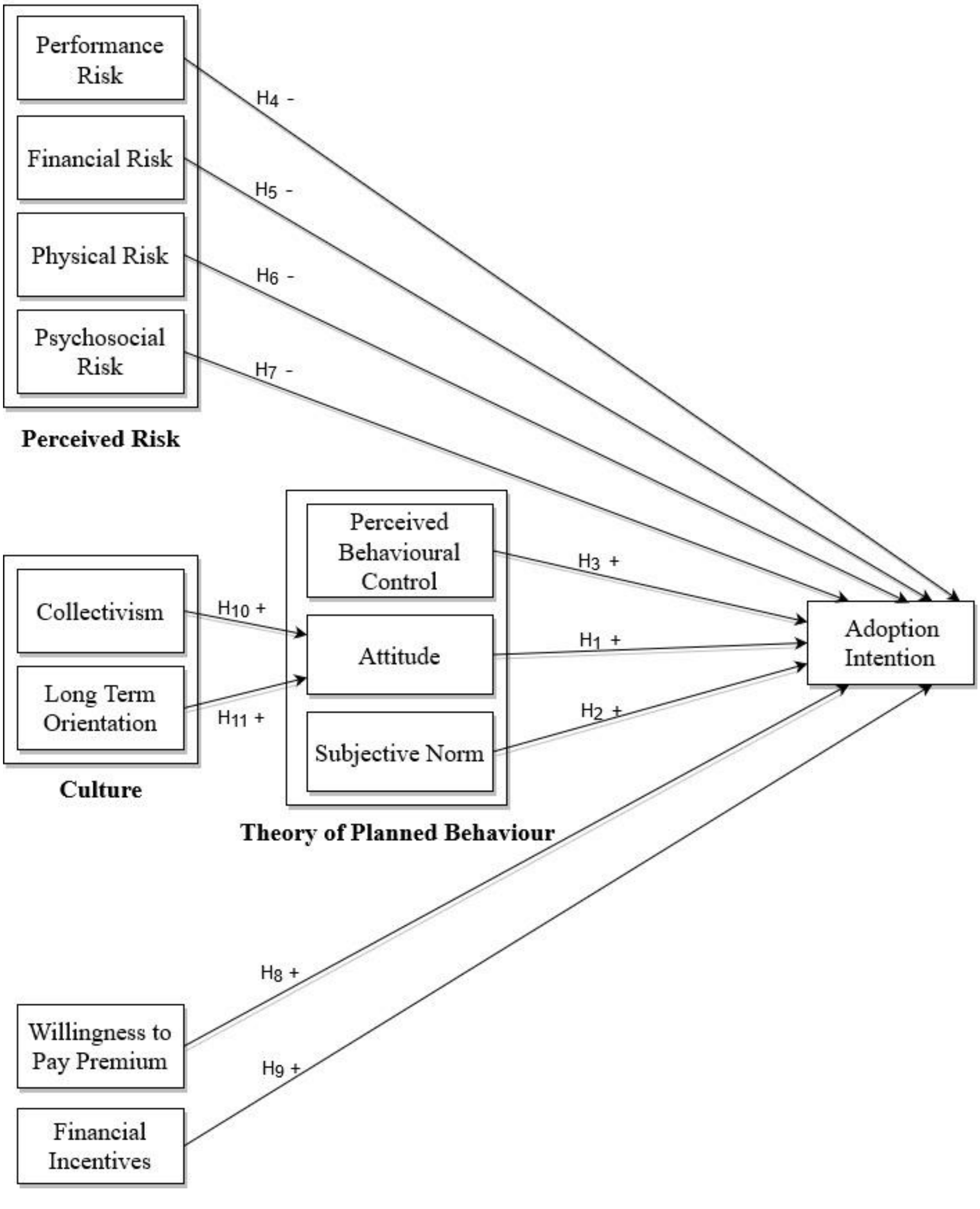


Figure 1. 2: Conceptual Model

(**Note**: + denotes positive influence; - denotes negative influence)

CHAPTER 2

RESEARCH METHODOLOGY

The study followed a quantitative research method that employed a self-administered survey questionnaire. The target population for the study was individuals with driving license as they would have enough familiarity and experience of driving vehicles (Sang & Bekhet, 2015). It is infeasible to obtain the list of all driving license holders in a country (Sang & Bekhet, 2015). Thus, non-probability purposive sampling was followed in the current study. A filter question was included in the questionnaire asking the respondents whether they have a valid driving license to ensure that only individuals with a valid driving license were chosen for the study. Data were collected anonymously and confidentiality of the data was assured to respondents to reduce common method variance issues as suggested by Podsakoff, MacKenzie, Lee, and Podsakoff (2003). Data collection was carried out between August 2019 and December 2020 among respondents across India. Multiple reminders were sent to participants to encourage them to complete the questionnaire in order to reduce non-response bias as suggested by Van Mol (2017).

The current study utilised various methods suggested by previous researchers to determine the required sample size. According to McQuitty (2004), it is important to determine the minimum sample size in order to achieve desired level of statistical power with a given model before collecting the data. Hoelter (1983) proposed a "critical sample size" of 200. In other words, a sample size of minimum 200 or above would provide sufficient statistical power for data analysis. The present study also utilised Slovin's Formula to calculate the desired sample size. Slovin's Formula could be represented as:

$$n = \frac{N}{1 + N(e)^2}$$

where n = Number of samples, N = Total population and e = Error tolerance. According to the Ministry of Road Transport & Highways (2022), the number of driving licenses holders (as on January 2022) in India is 15,98,50,002. Using Slovin's

Formula with e = 0.05, the sample size was calculated to be 399.99. Thus, the sample size calculation revealed that the required sample size was 400. Another generally agreed value is 10 participants for every free parameter estimated (Klin, 2015). There are 64 items in the measurement scales of the constructs, and the number of responses have to be greater than the minimum requirement of 640 (i.e., 64 * 10). Responses were collected from 738 participants, and incomplete responses were filtered out. Thus, the total number of responses considered for the analysis was 703.

2.1 Sample Characteristics

Out of 703 respondents, 78.8 per cent were male and 21.2 per cent were female. 13.5 per cent belonged to the age group 18-25, 48.9 per cent belonged to the age group 26-35, 27.7 per cent belonged to 36-45 age group, 6.5 per cent belonged to 46-55 age group, and 3.3 per cent belonged to above 55 age group. Regarding marital status, 40.4 per cent were single and 59.6 per cent were married. Regarding the highest educational qualification, 1.6 per cent were Secondary School (Class 9 to 10), 5.1 per cent had Diploma/10+2, 45.5 per cent had graduation, 34.0 per cent had a post-graduate degree, and the remaining 13.8 per cent had a doctoral degree or above. The monthly household income of 42.7 per cent respondents were up to Rs. 50000, 27.6 per cent were from Rs. 50,001 to Rs. 100,000, 18.1 per cent were from Rs. 100,001 to Rs. 150,000 and 11.7 per cent were above Rs. 150,000. 46.4 per cent of respondents were from urban region, 36.8 per cent from semi-urban region and 16.8 per cent from rural region. Out of 703 respondents, there were no cars in the household of 26.2 per cent, one car in the household of 47.1 per cent, two cars in the household of 22.8 per cent and more than three cars in the household of 4.0 per cent. 1.1 per cent had only 1 member in their family, 25.6 per cent had 2 to 3 members, 61.9 had 4 to 5 members, and 11.4 per cent had more than 5 members in their family. Regarding the daily distance travelled by car, 82.2 per cent travels less than 50 KM per day, 11.9 per cent travels 50 to 100 KM per day, 3.1 per cent travels 100 to 200 KM per day, and 2.7 per cent travels more than 200 KM per day.

Table 2.1: Sample characteristics

S.No	Items		No.	Per cent
1	Gender	Male	554	78.8
		Female	149	21.2
2	Age	18-25	95	13.5
		26-35	344	48.9
		36-45	195	27.7
		46-55	46	6.5
		Above 55	23	3.3
3	Marital status	Married	419	59.6
		Single	284	40.4
4	Educational Qualification	Secondary School (Class 9 to 10)	11	1.6
		Diploma/10+2	36	5.1
		Graduation	320	45.5
		Post-graduation	239	34.0
		Doctorate or above	97	13.8
5	Monthly Household Income	Up to 50,000	300	42.7
		From 50,001 to 100,000	194	27.6
		From 100,001 to 150,000	127	18.1
		150,001 and above	82	11.7
6	Location	Urban	326	46.4
		Semi-urban	259	36.8
		Rural	118	16.8
7	Number of cars in the household	0	184	26.2
		1	331	47.1
		2	160	22.8
		3 or more	28	4.0
8	Family size	1 member	8	1.1
		2-3 members	180	25.6
		4-5 members	435	61.9
		More than 5 members	80	11.4
9	Daily distance travelled by car	Less than 50 km	578	82.2
		50-100 km	84	11.9
		100-200 km	22	3.1
		More than 200 km	19	2.7
10	Frequency of long trips in car	Low frequency (holidays, occasional trips)	497	70.7
		High frequency	162	23.0
		Never	44	6.3
11	Knowledge about the benefits	Completely know the benefits	218	31.0
		Somewhat know the benefits	432	61.5
		Don't know the benefits	53	7.5

Regarding the frequency of long trips in cars (a distance of over 200km), 70.7 per cent showed low frequency (holidays, occasional trips), 23.0 per cent showed high frequency, and 6.3 per cent never uses cars for long trips. 31.0 per cent believed that they completely know the benefits, 61.5 per cent believed that they somewhat know the benefits, and 7.5 per cent believed that they do not know the benefits of using an electric car.

2.2 Conceptualisation and Operationalisation of Variables

- Following the definition of Attitude by Ajzen (1991), Attitude towards electric car could be defined as "a psychological path that determines favour or disfavour of an individual towards electric car". The measures for attitude towards electric cars were adapted from Adnan et al. (2018). Items were measured using 5-point Likert scale with "1" anchored as "Strongly disagree" and "5" anchored as "Strongly agree".
- Perceived Behavioural Control (PBC) is related to the perceived ability as well as the external source constraints and facilitators of the behaviour (Ajzen, 1991). PBC measures were adapted from the scale developed by Paul, Modi and Patel (2016). Items were measured using 5-point Likert scale with "1" anchored as "Strongly disagree" and "5" anchored as "Strongly agree".
- Subjective norms are the perceived social pressure an individual faces when deciding whether to behave in a certain way (Park, 2000). Measures for subjective norms were adapted from the scale developed by Moons and De Pelsmacker (2012). Items were measured using 5-point Likert scale with "1" anchored as "Strongly disagree" and "5" anchored as "Strongly agree".
- Adoption intention could be defined as "the willingness and intention of an individual to adopt electric cars". The measures for adoption intention towards electric car were adapted from the scale developed by Mohiuddin, Al Mamun, Syed, Masud and Su (2018). Items were measured using 5-point Likert scale with "1" anchored as "Strongly disagree" and "5" anchored as "Strongly agree".

- Financial risk refers to “disappointment about value for the money, waste, or loss in the event of product malfunction” (Pueschel et al., 2017). Measures for Financial risk were adapted from Biswas, Biswas, and Das (2006) and Shapiro, Reams, and So (2019). The items of financial risk were measured using 5-point Likert scale with “1” anchored as “not at all risky” and “5” anchored as “extremely risky”.
- Physical risk involves the threat to consumer health and safety (Pueschel et al., 2017). Measures for Physical risk were adapted from Petschnig, Heidenreich, and Spieth (2014). The items of Physical risk were measured using 5-point Likert scale with “1” anchored as “Strongly disagree” and “5” anchored as “Strongly agree”.
- Psychosocial risk refers to the possibility for potential loss of self-esteem and/or social esteem of consumers as a result of their purchase decisions (Mitchell & Harris, 2005). Measures for Psychosocial Risk were adapted from the scale developed by Pueschel et al. (2017). Items were measured using 5-point Likert scale with “1” anchored as “Strongly disagree” and “5” anchored as “Strongly agree”.
- Performance risk relates to situations in which the product fails to perform as expected (Pueschel et al.,2017). Measures for Performance Risk were adapted from Antioco and Kleijnen (2010). The items of Performance Risk were measured using 5-point Likert scale with “1” anchored as “Very little risk” and “5” anchored as “A great deal of risk”.
- The variable “Financial incentives” refers to the perception of consumers regarding various financial incentives provided by government. Measures for government financial incentives were adapted from Kim, Oh, Park and Joo (2018). The items of financial incentives were measured using 5-point Likert scale with “1” anchored as “Strongly disagree” and “5” anchored as “Strongly agree”.
- Willingness-to-Pay Premium could be defined conceptually as consumers being prepared to pay more for electric cars than for comparable conventional cars. Measures for Willingness to Pay Premium were adapted from the scale developed by Al Mamun, Fazal, Ahmad, Yaacob,

and Mohamad (2018). Items were measured using 5-point Likert scale with “1” anchored as “Strongly disagree” and “5” anchored as “Strongly agree”.

- Collectivism is the degree to which people in a society are integrated into groups (Hofstede, 2011). Measures for Collectivism were adapted from the scale developed by Sreen, Purbey and Sadarangani (2018). Items were measured using 5-point Likert scale with “1” anchored as “Strongly disagree” and “5” anchored as “Strongly agree”.
- Long-Term Orientation “stands for the fostering of virtues oriented toward future rewards, in particular, perseverance and thrift” (Hofstede, 2001). Measures for Long term orientation were adapted from the scale developed by Sreen, Purbey and Sadarangani (2018). Items were measured using 5-point Likert scale with “1” anchored as “Strongly disagree” and “5” anchored as “Strongly agree”.

2.3 Test Administration

Survey instruments designed for this study were distributed among individuals who possess driving license. All the questions in the questionnaire were in the English language. The survey instrument consisted of 3 sections namely – Section A, Section B and Section C. Section A consisted of questions regarding the demographic and general information of the respondents, such as age, gender, monthly income, number of cars in the household etc. Section B and C consisted of 5-point Likert scale questions to measure various constructs in the study. Multi-item measures were adopted from previous studies and tailored to fit the current study’s context. Content validity was ensured in the form of face validity with the help of 4 experts (2 from academia and 2 from industry) so that the scale items sufficiently represented the constructs in the study. In addition, a pretest was conducted with 30 participants before initiating the final survey.

2.4 Statistical Tools and Techniques for Data Analysis

After data collection, the Statistical Package for Social Sciences (SPSS) version 23.0 and Analysis of Moments Structure (AMOS) version 23.0 were used to analyse the data. The statistical analyses such as descriptive statistics, developing the correlation matrix, and calculating Cronbach's alphas of the various measures used in the study were performed using SPSS. The measurement model was assessed using AMOS 23.0. For this purpose, a variety of Goodness-of-Fit indices provided by AMOS 23.0 (Arbuckle & Wothke, 1999) was utilised. The structural model based on the hypotheses was analysed and tested using AMOS 23.0.

CHAPTER 3

DATA ANALYSIS AND RESULTS

3.1 Introduction

The previous chapter described the characteristics of population, sample, measuring instruments and procedure followed for data collection. This chapter deals with the descriptive statistics, reliability assessment, validity assessment, confirmatory factor analysis and hypotheses testing using structural equation modelling.

3.2 Structural Equation Modelling

Structural Equation Modelling (SEM) is a statistical technique used to assess the relationship between multiple independent variables and dependent variables. SEM involves Measurement model (also termed as Confirmatory Factor Analysis) and Structural model. Measurement model and structural model in SEM combinedly facilitate the verification of ‘causal’ relationships between variables.

The current study assessed the proposed model fit to the data using the SEM technique. The proposed model consisted of Attitude towards electric cars (ATT), Subjective Norm (SN), Perceived Behavioural Control (PBC), Willingness to Pay Premium (WPP), Financial Incentives (FI), Collectivism (COL), Long-Term Orientation (LTO), Performance Risk (PR), Financial Risk (FIR), Physical Risk (PHY), Psycho-social Risk (PSR) and Adoption Intention (AI).

The present study utilised the following approaches for model testing and analyses. First, the proposed model analyses were carried out utilising covariance and most widely used Maximum Likelihood method with AMOS 23.0. Second, the model development strategy was followed through model respecification procedure that aimed at identifying the sources of misfit and then creating a model that have a better fit to the data (Byrne, 2001). Third, model with structural relationships was assessed to test and verify various hypothesised relationships in the study.

3.3 Measurement Model

SEM has two distinct components, namely measurement model and structural model. Measurement model focuses on the constructs (latent unobserved variables) and their indicators (observed variables). Confirmatory Factor Analysis (CFA) is used to assess the measurement model. Within the framework of SEM, CFA focuses on the relationship between factors and their measured variables (Byrne, 2001).

Confirmatory measurement models need to be evaluated and respecified prior to final measurement, and then structural equation models should be examined (Anderson & Gerbing, 1988). Thus, before testing the overall measurement models, each construct of the model must be evaluated and analysed individually using a series of model identification steps. After ensuring that each construct individually has an acceptable fit to the model, all the constructs in the model should be evaluated together to generate a final model that is both meaningful and statistically acceptable. Measurement models are assessed utilising Goodness-of-Fit measures. As a whole, it is to be understood that the measurement model needs to be approved first before the testing and evaluation of structural model (Garson, 2005).

Following Bollen (1990), the current study utilised different indices to evaluate the model fit. This is because there are chances for a model to show acceptable level on a specific fit index while not having adequate level in other indices. The indices used in this study were chosen as recommended by Hu and Bentler (1995) and Hair, Black, Babin, Anderson, and Tatham (2006). Both measurement model and structural model need to have acceptable fit in the selected indices to ensure the Goodness-of-Fit for empirical data. As suggested by McIntosh (2007), the first overall test of model fit considered was the Chi-square ($\chi2$) test. It is one of the most common methods utilised to assess the Goodness-of-Fit of model. A low $\chi2$ value with non-significance would indicate a good model fit. Chi-square should not be significant to achieve a good model fit. This is because $\chi2$ test involves assessment of actual and predicted matrices. Thus, non-significance of $\chi2$ values shows that there is no considerable difference between actual and predicted matrices (Hair, Anderson, Tatham & Black, 1998).

However, chi-square test has a limitation. Chi-square test is extremely sensitive to sample size (Bentler, 1990), especially if the observations are larger than

200. Another way of using $\chi2$ statistics is to utilise the ratio of $\chi2$ to the degrees of freedom (Joreskog & Sorbom, 1993). A low $\chi2$ value relative to its degree of freedom indicate a good model fit. Thus, chi-square normalised by degrees of freedom ($\chi2/df$) was also utilised in the study. The $\chi2/df$ value should be less than 3.0 for acceptable model fit (Hair et al., 2006; Kline, 1998).

In addition to chi-square test, at least one incremental fit index, one absolute fit index and one badness-of-fit index need to be mentioned (Hair et al., 2006). Absolute fit measures and incremental fit measures are two important types of overall fit measures (Byrne, 1998; Hair et al., 1998; Hoyle & Panter, 1995; Hu & Bentler, 1995). Absolute fit indices are utilised to analyse how well a priori conceptual model fits the sample data. Incremental fit indices compare a target model to a more restricted, nested baseline model to evaluate the proportionate fit. This index deals with the degree to which a model is superior to an alternative model and could be used to measure 'Goodness-of-Fit' (Hoyle & Panter, 1995).

An absolute fit index used in the study is Goodness-of-Fit Index (GFI) and it compares the hypothesised model with no model at all (Hu & Bentler, 1995). GFI value could range from 0 to 1.00, with values near 1.00 showing a good model fit. Fan, Thompson, and Wang (1999) remind the researchers to be cautious while using GFI as it is sensitive to sample size. Similarly, as incremental or comparative indices, the study have utilised Tucker-Lewis Index (TLI) and Comparative Fit Index (CFI). These indices are obtained by comparing the hypothesised model with some standard model. The values of TLI and CFI could also range between 0 and 1.00, which are estimated based on the comparison of the hypothesised model with an independence model. Value greater than 0.9 is considered as the acceptable level for well-fitted models (Bentler, 1990). Larger values demonstrate that the model under consideration have greater improvement compared to alternative model (Hoyle & Panter, 1995; Hu & Bentler, 1995).

Regarding Badness-of-Fit index, Root Mean Square Error of Approximation (RMSEA) was utilised. RMSEA was used as it was found to provide consistent results across different estimation approaches (Sugawara & MacCallum, 1993). RMSEA is a very useful criterion in measuring the model fit. It estimates the discrepancy between the observed and estimated covariance matrices per degrees of freedom (Steiger, 1990). RMSEA calculates the discrepancy based on the population, and not the sample. Thus, the value of this index is expected to better reflect the population and is unaffected by sample size. The values of RMSEA may range from 0 to 1.00. A value of 0.06 for RMSEA shows a good fit, values up to 0.08 show reasonable fit and values between 0.08 to 0.10 show a mediocre fit.

Based on the above discussions, along with chi-square and $\chi2$/df values, model fit for the current study was assessed utilising multiple indices namely: GFI, CFI, TLI, and RMSEA (Hu & Bentler, 1999). Following the common practice, acceptable model fit is indicated by values higher than 0.90 for GFI, CFI, TLI and a value of less than .08 for RMSEA. However, a cut-off value close to .95 for TLI, CFI; and a cut-off value close to .06 for RMSEA are needed to support that there is a relatively good fit between the hypothesized model and the observed data (Hu & Bentler, 1999). Unlike the CFI, the TLI is non-normed and its value can fall outside the range of 0 to 1.0. However, values approaching 1.0 are interpreted as good model fit (Kline, 2005).

Table 3. 1: Summary of recommended fit indices for the models

Fit Index	Recommended Value
Absolute Fit Measures	
$\chi2$/df	$\leq$3
GFI	$\geq$.90
RMSEA	$\leq$.06 or .08
Incremental Fit Measures	
TLI	$\geq$.95 or .90
CFI	$\geq$.95 or .90

3.4 Confirmatory Factor Analysis

CFA was utilised to assess the measurement model fit and unidimensionality. The current study followed a two-step approach proposed by Anderson and Gerbing (1988). The measurement model was initially tested, modified and confirmed using CFA for validity and reliability. This helped identify the model that best fit the data using SEM to proceed with hypotheses testing. This approach is highly preferred as structural analyses are often not reliable if the measurement model is without enough validity and reliability (Hair et al., 2006).

Gerbing and Anderson (1988) stressed the importance of unidimensionality in the scale development process. They asserted that traditional exploratory analyses (such as factor analysis and item-total correlation) fail to measure unidimensionality directly as they are not theory-based analysis. To address this limitation, Confirmatory Factor Analysis (CFA) was utilised to assess the measurement model fit and unidimensionality.

It is important to discuss about identification issue and model specification while discussing about CFA. The identification issue in SEM is related to whether there are adequate pieces of information to identify a solution for a set of structural equations (Hair et al., 2006). It is crucial to ascertain the identification status of a hypothesised model by examining the number of degrees of freedom associated with the model (Byrne, 2001) provided in the parameter summary of the AMOS output. Regarding specification of the latent constructs, the loading of one indicator for each construct was set as 1.00 in the model to create a scale for latent construct. This was done automatically through the features available in AMOS software.

3.4.1 Confirmatory Factor Analysis for Attitude

The measurement scale for Attitude (ATT) consists of 7 items. All 7 items were considered as one factor and entered into CFA analysis process. First, the measurement model should display a good model fit and should satisfy the criteria for various fit indices as explained earlier. The initial measurement model (CFA1) for Attitude (χ^2 = 149.583, χ^2/df=10.685, GFI=.904, TLI=.851, CFI=.901, RMSEA=.155) did not provide an adequate model fit for the empirical data.

Table 3. 2: Fit indices result for ATT

Model	Model Fit Indices						Items deleted	Reason for deletion
	χ2/df	*p*	GFI	TLI	CFI	RMSEA		
CFA1	10.685	.000	.904	.851	.901	.155	ATT2	LFL, LMI
CFA2	13.902	.000	.905	.850	.910	.179	ATT6	LMI
CFA3	1.410	.217	.993	.996	.998	.032	-	-

Note: LFL = Low Factor Loading; LMI = Large Modification Index

The model chi-square was 149.583 with p-value = .001. The significant p-value did not show that the observed covariance matrix matches the estimated covariance matrix from the empirical data (Hair et al., 2006). Nevertheless, other model fit indices should also be considered as the chi-square statistical test is sensitive to sample size (Byrne, 2001).

The normed chi-square (χ^2/df) value for CFA1 showed 10.685, which was higher than the desired cut-off value of 3.0 (Hair et al., 2006). The GFI value was .904, CFI was .901, and TLI was 0.851. The GFI, CFI and TLI values should be higher than the recommended level of 0.9. The TLI values did not satisfy the recommended criteria, thus showing inadequate model fit for further analysis. Thus, it was clear that some modifications were required to achieve a model that would better fit with the data. The measurement model may be modified by assessing the standardised loading estimates (path estimates linking constructs to indicators), modification indices and standardised residuals (Hair et al., 2006). Each of these measures were considered along with model fit indices to determine if respecification is required.

Firstly, the standardized loading estimates were assessed to verify whether they are greater than 0.5 (Hair et al., 2006). Secondly, the standardized residuals are considered. The standardized residuals represent the difference between the observed covariance and the estimated covariance with smaller fitted residuals indicating good model fit (Lu, Lai, & Cheng, 2007). Based on the recommendation of Hair et al. (2006), items associated with a standardised residual greater than |4| were dropped. Attention was also given to those items with standardised residuals between |2.5| and |4| by checking modification indices and loading estimates to detect any other problems associated with the pair items. Thirdly, modification indices were considered as an indication of any possible respecification of the model. The MI value represents the expected drop in overall chi-square value if a single parameter is to be freed and the model re-estimated in a subsequent run (Byrne, 2001). Generally, MI value of approximately 4 or greater indicates that the model fit could be improved significantly by estimating the corresponding path (Hair et al., 2006).

Firstly, the standardized loading estimate for the item ATT2 was found to be .367, which was far lower than the minimum desired value of 0.5 (Hair et al., 2006).

Hence, ATT2 was excluded from the further analysis based on its low standardized loading estimate. Next, standardized residuals for the dataset were assessed to identify potential model respecification. The standardized residual between ATT6 and ATT7 was 3.683, which was near to the higher side of the cut-off value (4). This suggests that covariance estimates of ATT6 and ATT7 could be more accurate. Theoretically, the items "I like electric car because it reduces carbon emission" and "I believe that electric cars help to save nature and its resources" seemed to be more closely related. Thus, it was decided to closely look at the items ATT6 and ATT7 to check for other potential problems associated with these items. Next, MI associated with each constrained path was considered. A review of the MIs for the regression weights (factor loadings) of ATT6 revealed a cross-loading with MI = 40.2. The MI associated with ATT6 supported the observation from the standardized residuals that ATT6 could emerge as a potential item for deletion. Thus, ATT6 was removed from further analysis.

After these modifications, the fit indices for the final CFA model (CFA3) improved greatly (X^2 = 7.050, X^2/df = 1.410, GFI = .993, TLI = .996, CFI = .998, RMSEA = .032). The revised measurement model fits the data well (Figure 3.1). The chi-square value was 7.050 with insignificant p-value (p=.217). The chi-square normalized by degrees of freedom (X^2/df) also showed an acceptable ratio of 1.410. The three fit indices for GFI, TLI and CFI were substantially higher than the .90 threshold for acceptability. Lastly, the RMSEA value was also found to be less than the cut-off value of .06 for a good model fit.

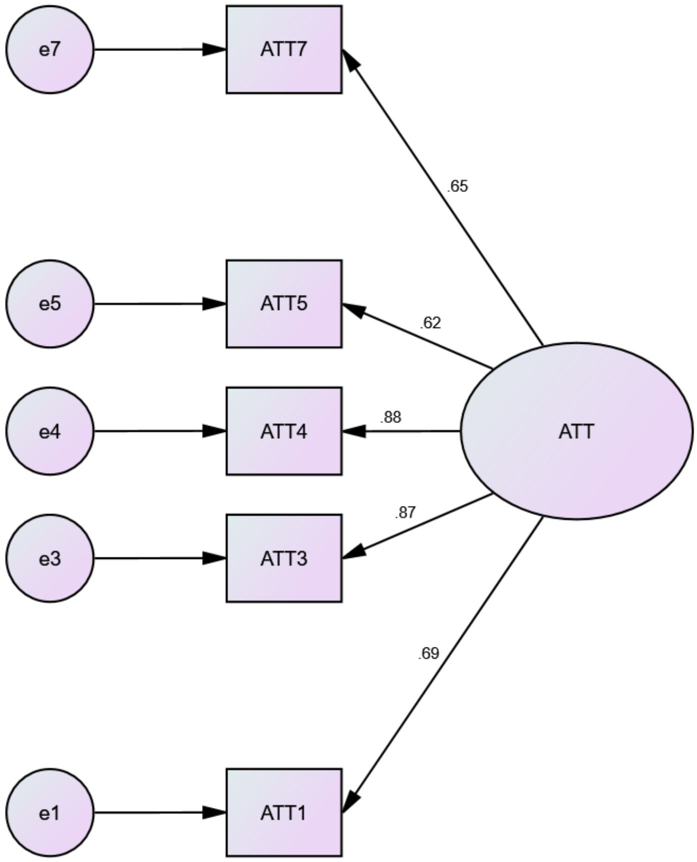


Figure 3. 1: Final standardized CFA for ATT with 5 items

(**Note**: ATT = Attitude)

3.4.2 Confirmatory Factor Analysis for Willingness to Pay Premium

The measurement scale for Willingness to Pay Premium (WPP) consists of 6 items. All the 6 items were considered as one factor and entered into CFA analysis process. The results of the initial estimation of the proposed model were acceptable for a well-fitting model.

Table 3. 3: Fit indices result for WPP

Model	Model Fit Indices						Items deleted	Reason for deletion
	$\chi 2$/df	*p*	GFI	TLI	CFI	RMSEA		
CFA1	2.508	.007	.981	.984	.990	.061	-	-

The initial measurement model (CFA1) for WPP (X^2 = 22.573, X^2/df = 2.508, GFI = .981, TLI = .984, CFI = .990, RMSEA = .061) provided an adequate model fit for the empirical data. The chi-square normalized by degrees of freedom (X^2/df) also showed an acceptable ratio of 2.508. The three fit indices for GFI, TLI and CFI were substantially higher than the .90 threshold for acceptability. Lastly, the RMSEA value was also found to be less than the cut-off value of .08 for a good model fit. Thus, the finalized measurement model fit the data well (Figure 3.2)

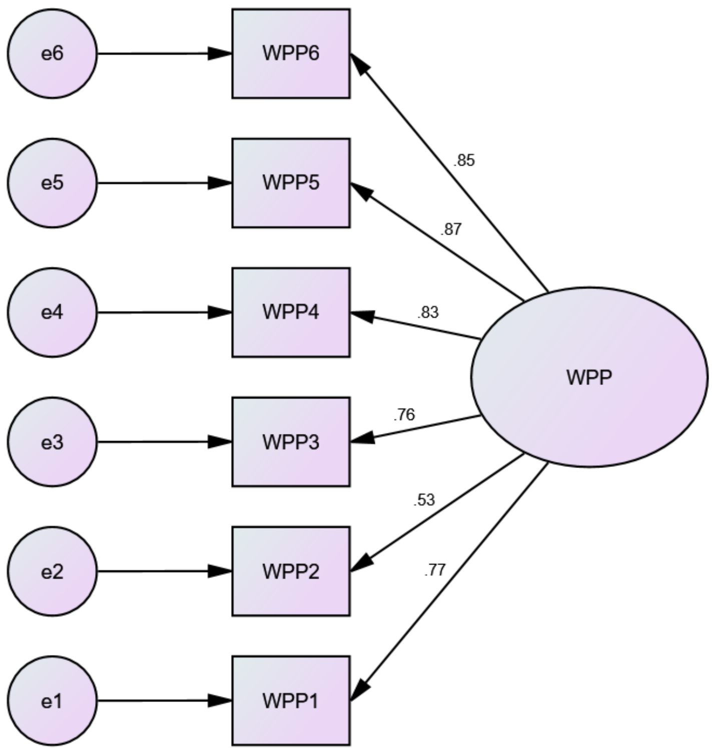


Figure 3. 2: Final standardized CFA for WPP with 6 items

(**Note**: WPP = Willingness to Pay Premium)

3.4.3 Confirmatory Factor Analysis for Collectivism

The measurement scale for Collectivism (COL) consists of 6 items. All the 6 items were considered as one factor and entered into CFA analysis process. First, the measurement model should display a good model fit and should satisfy the criteria for various fit indices as explained earlier. The initial measurement model (CFA1) for Collectivism (X^2 = 29.327, X^2/df = 3.259, GFI = .978, TLI = .898, CFI = .939, RMSEA = .075) did not provide an adequate model fit for the empirical data.

Table 3. 4: Fit indices result for COL

Model	Model Fit Indices						Items deleted	Reason for deletion
	$\chi 2$/df	*p*	GFI	TLI	CFI	RMSEA		
CFA1	3.259	.001	.978	.898	.939	.075	COL6	LFL, LMI
CFA2	1.946	.083	.991	.967	.984	.048	-	-

Note: LFL = Low Factor Loading; LMI = Large Modification Index

The model chi-square was 29.327 with p-value = .001. The normed chi-square (χ^2/df) value for CFA1 showed 3.259, which was slightly higher than the desired cut-off value of 3.0 (Hair et al., 2006). RMSEA value was .075, which was less than the cut-off value of .08 for a good model fit. The GFI value was .978, TLI was .898, and CFI was .939. The GFI, CFI and TLI values should be higher than the recommended level of 0.9. The TLI values did not satisfy the recommended criteria, thus showing inadequate model fit for further analysis. Thus, it was clear that some modifications were required to achieve a model that would better fit with the data.

Firstly, the standardized loading estimates for the item COL6 was found to be .314, which was far lower than the minimum desired value of 0.5 (Hair et al., 2006). In addition, a review of the MIs for the regression weights (factor loadings) of COL6 revealed a cross-loading with MI = 11.01. Hence, COL6 was excluded from the further analysis based on its low standardized loading estimate.

After these modifications, the fit indices for the final CFA model (CFA2) improved (X^2 = 9.731, *p*-value = .083, X^2/df = 1.946, GFI = .991, TLI = .967, CFI = .984, RMSEA = .048). The revised measurement model fit the data well (Figure 3.3). The chi-square value was 9.731 with insignificant p-value (p=.083). The chi-square normalized by degrees of freedom (X^2/df) also showed an acceptable ratio of 1.946. The three fit indices for GFI, TLI and CFI were substantially higher than the .90 threshold for acceptability. Lastly, RMSEA value was also found to be less than the cut-off value of .06 for a good model fit.

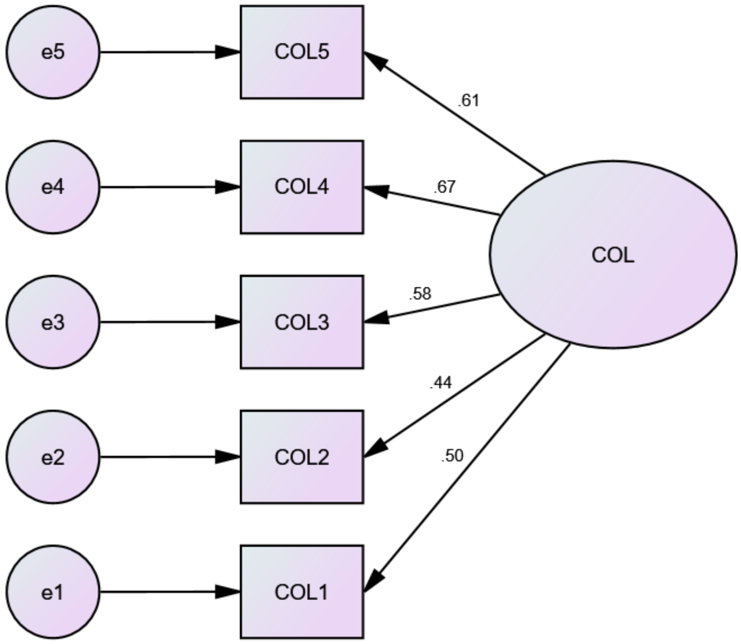


Figure 3. 3: Final standardized CFA for COL with 5 items

(**Note**: COL = Collectivism)

3.4.4 Confirmatory Factor Analysis for Physical Risk

The measurement scale for Physical Risk (PYR) consists of 5 items. All 5 items were considered as one factor and entered into CFA analysis process. First, the measurement model should display a good model fit and should satisfy the criteria for various fit indices as explained earlier. The initial measurement model (CFA1) for Collectivism (X^2 = 149.880, X^2/df = 29.976**,** GFI = .868, TLI = .648, CFI = .824, RMSEA = .268) did not provide an adequate model fit for the empirical data.

Table 3. 5: Fit indices result for PYR

Model	Model Fit Indices						Items deleted	Reason for deletion
	$\chi 2$/df	*p*	GFI	TLI	CFI	RMSEA		
CFA1	29.976	.000	.868	.648	.824	.268	PYR4	LMI, HSR
CFA2	3.292	.037	.992	.973	.991	.075	-	-

Note: LMI = Large Modification Index; HSR = High Standardized Residual

The model chi-square was 149.880 with p-value = .000. The normed chi-square (χ^2/df) value for CFA1 showed 29.976, which was higher than the desired cut-off value of 3.0 (Hair et al., 2006). RMSEA value was .268, which was higher than the cut-off value of .08 for a good model fit. The GFI value was .868, TLI was .648, and CFI was .824. The GFI, CFI and TLI values should be higher than the recommended level of 0.9. The GFI, CFI and TLI values did not satisfy the recommended criteria, thus showing inadequate model fit for further analysis. Thus, it was clear that some modifications were required to achieve a model that would better fit with the data.

Firstly, the standardized residuals for the dataset were assessed to identify potential model respecification. The standardized residual between PYR4 and PYR5 was 5.452, which was higher than the cut-off value (4). This suggests that covariance estimates of PYR4 and PYR5 could be more accurate. Theoretically, the items "There exists low risk of injury for persons using electric cars" and "Electric cars represent a low accident risk for passengers" seemed to be more closely related. Thus, it was decided to closely look at the items PYR4 and PYR5 to check for other potential problems associated with these items.

Next, MI associated with each constrained path was considered. A review of the MIs for the regression weights (factor loadings) of PYR4 revealed a cross-loading with MI = 70.756. The MI associated with PYR4 supported the observation from the standardized residuals that PYR4 could emerge as a potential item for deletion. Thus, PYR4 was removed from further analysis.

After these modifications, the fit indices for the final CFA model (CFA2) improved greatly (X^2 = 6.584, X^2/df = 3.292**,** GFI = .992, TLI = .973, CFI = .991, RMSEA = .075). The revised measurement model fit the data well (Figure 3.4). The chi-square value was 6.584 with p-value = .037. The chi-square normalized by degrees of freedom (X^2/df) also showed an acceptable ratio of 3.292. The three fit indices for GFI, TLI and CFI were substantially higher than the .90 threshold for acceptability. Lastly, RMSEA value was also found to be less than the cut-off value of .08 for a good model fit.

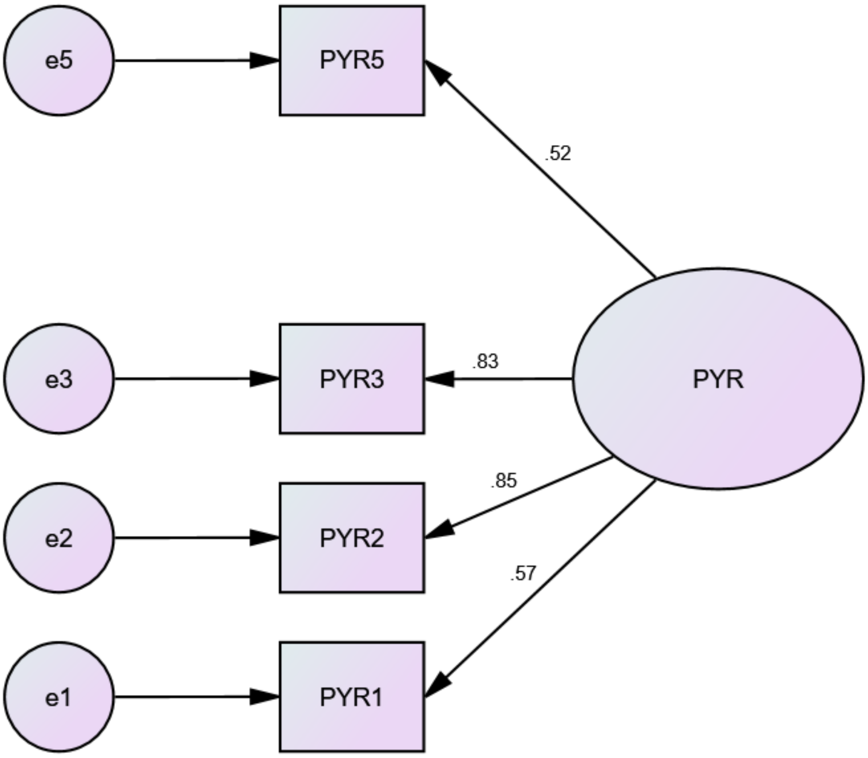


Figure 3. 4: Final standardized CFA for PYR with 4 items

(**Note**: PYR =Physical Risk)

3.4.5 Confirmatory Factor Analysis for Psychosocial Risk

The measurement scale for Psychosocial Risk (PSR) consists of 6 items. All the 6 items were considered as one factor and entered into CFA analysis process. First, the measurement model should display a good model fit and should satisfy the criteria for various fit indices as explained earlier. The initial measurement model (CFA1) for Psychosocial Risk (X^2 = 292.617, X^2/df = 32.513, GFI = .840, TLI = .449, CFI = .669, RMSEA = .280) did not provide an adequate model fit for the empirical data.

Table 3. 6: Fit indices result for PSR

Model	Model Fit Indices						Items deleted	Reason for deletion
	$\chi 2$/df	*p*	GFI	TLI	CFI	RMSEA		
CFA1	32.513	.000	.840	.449	.669	.280	PSR6	LFL, LMI, HSR
CFA2	1.792	.111	.991	.985	.993	.044	-	-

Note: LFL = Low Factor Loading; LMI = Large Modification Index; HSR = High Standardized Residual

The model chi-square was 292.617 with p-value = .000. The normed chi-square (χ^2/df) value for CFA1 showed 32.513, which was higher than the desired cut-off value of 3.0 (Hair et al., 2006). The GFI value was .840, TLI was .449, and CFI was .669. The GFI, CFI and TLI values should be higher than the recommended level of 0.9. The GFI, CFI and TLI did not satisfy the recommended criteria, thus showing inadequate model fit for further analysis. Thus, it was clear that some modifications were required to achieve a model that would better fit with the data.

Firstly, the standardized loading estimates for the item PSR6 was found to be .378, which was lower than the minimum desired value of 0.4. Next, standardized residuals for the dataset were assessed to identify potential model respecification. The standardized residual between PSR5 and PSR6 was 11.399, which was higher than the cut-off value of |4|. This suggests that covariance estimates of PSR5 and PSR6 could be more accurate. Theoretically, the items “I would like to be sure not to receive negative criticism from people I meet” and “I would like to be sure not to receive negative criticism from my family” seemed to be more closely related. Thus, it was decided to closely look at the items PSR5 and PSR6 to check for other potential problems associated with these items. Next, MI associated with each constrained path was considered. A review of the MIs for the regression weights (factor loadings) of PSR6 revealed a cross-loading with MI = 161.033. The MI associated with PSR6 supported the observation from the standardized residuals that PSR6 is a potential item for deletion. Thus, PSR6 was removed from further analysis.

After these modifications, the fit indices for the final CFA model (CFA2) improved greatly (X^2 = 8.960, X^2/df = 1.792, GFI = .991, TLI = .985, CFI = .993, RMSEA = .044). The revised measurement model fit the data well (Figure 3.5). The chi-square value was 8.960 with insignificant p-value (p = .111). The chi-square normalized by degrees of freedom (X^2/df) also showed an acceptable ratio of 1.792. The three fit indices for GFI, TLI and CFI were substantially higher than the .90 threshold for acceptability. Lastly, RMSEA value was found to be .044 which was less than the cut-off value of .06 for a good model fit.

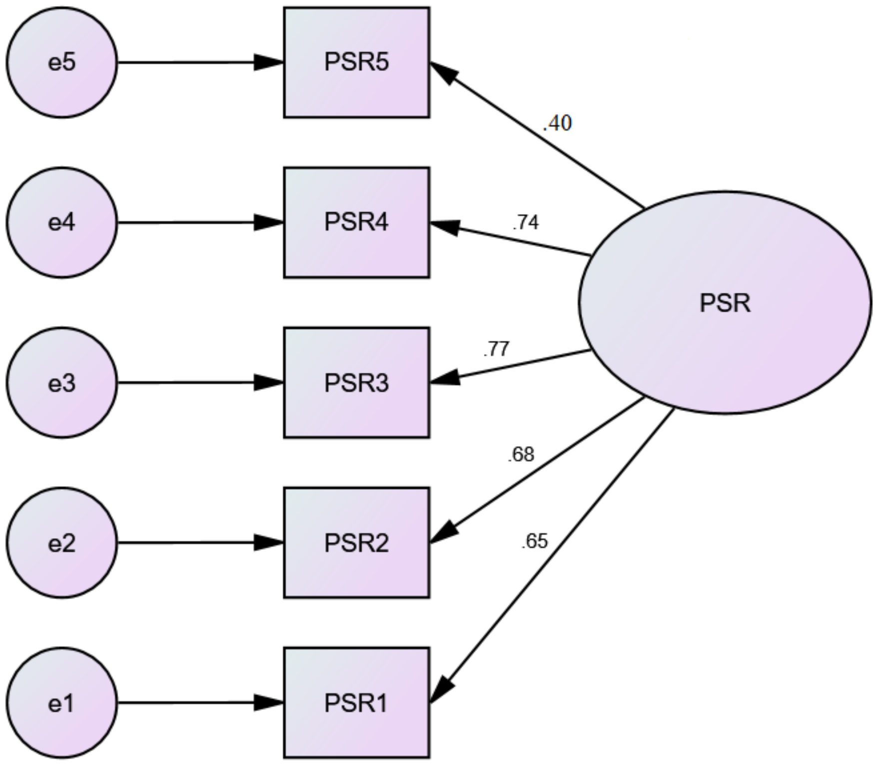


Figure 3. 5: Final standardized CFA for PSR with 5 items

(**Note**: PSR = Psychosocial Risk)

3.4.6 Confirmatory Factor Analysis for Subjective Norm

The measurement scale for Subjective Norm (SN) consists of 7 items. All 7 items were considered as one factor and entered into CFA analysis process. First, the measurement model should display a good model fit and should satisfy the criteria for various fit indices as explained earlier. The initial measurement model (CFA1) for Subjective Norm (X^2 = 237.274, *p*-value = .000, X^2/df = 16.948, GFI = .839, TLI = .579, CFI = .719, RMSEA = .199) did not provide an adequate model fit for the empirical data.

Table 3. 7: Fit indices result for SN

Model	Model Fit Indices						Items deleted	Reason for deletion
	$\chi2$/df	*p*	GFI	TLI	CFI	RMSEA		
CFA1	16.948	.000	.839	.579	.719	.199	SN3	LFL, LMI
CFA2	11.953	.000	.914	.755	.853	.165	SN1	LFL, LMI
CFA3	5.085	.000	.975	.931	.966	.101	SN4	LFL, LMI
CFA4	6.729	.001	.984	.940	.980	.119	-	-
CFA5	1.467	.226	.998	.995	.999	.034	-	-

Note: LFL = Low Factor Loading; LMI = Large Modification Index

The model chi-square was 237.274 with p-value = .000. The normed chi-square (χ^2/df) value for CFA1 showed 16.948, which was higher than the desired cut-off value of 3.0 (Hair et al., 2006). RMSEA value was .199, which was higher than the cut-off value of .08. The GFI value was .839, TLI was .579, and CFI was .719. The GFI, CFI and TLI values did not satisfy the recommended criteria as the values were lower than the recommended level of 0.9. Thus, it was clear that some modifications were required to achieve a model that shows adequate model fit for further analysis.

The standardized loading estimates for the item SN1, SN3 and SN4 were .065, .006 and .177 respectively. These values were far lower than the minimum desired value of 0.4. In addition, a review of the MIs for the regression weights (factor loadings) revealed evidence of misspecification associated with items SN1, SN3 and SN4. Thus, three rounds of CFA (CFA1 to CFA3) were performed by removing the items SN1, SN3 and SN4 one after the other on the basis of the results shown by standardised loading estimates, standardised residuals and modification indices.

The fourth measurement model (CFA4) for SN (X^2 = 13.459, χ^2/df = 6.729, GFI = .984, TLI = .940, CFI = .980, RMSEA = .119) provided a good model fit, except for χ^2/df and RMSEA. χ^2/df value from CFA4 was higher than the cut-off value of 3, and RMSEA value from CFA4 was higher than the cut-off value of .06. Thus, further respecification is required to achieve an adequate model fit for further analysis. Considering the modification indices, a covariance was drawn between the error terms of SN2 and SN5 (e2 $\leftarrow\rightarrow$e5). This resulted in an adequate fitting model (CFA5) as shown in Table 3.7.

After these modifications, the fit indices for the final CFA model (CFA5) improved greatly (X^2 = 1.467, *p*-value = .226, X^2/df = 1.467, GFI = .998, TLI = .995, CFI = .999, RMSEA = .034). The revised measurement model is illustrated in Figure 3.6. The standardized loading estimate of the item SN2 was .32, which was slightly less than the cut-off value of 0.4. However, it was decided to not delete SN2 and to give additional attention to the item during further analysis as there were no other associated problems. The chi-square value was 1.467 with insignificant p-value (p = .226). The chi-square normalized by degrees of freedom (X^2/df) also showed an acceptable ratio of 1.467. The three fit indices for GFI, TLI and CFI were substantially higher than the .90 threshold for acceptability. Lastly, RMSEA value was found to be .034 which was less than the cut-off value of .06 for a good model fit.

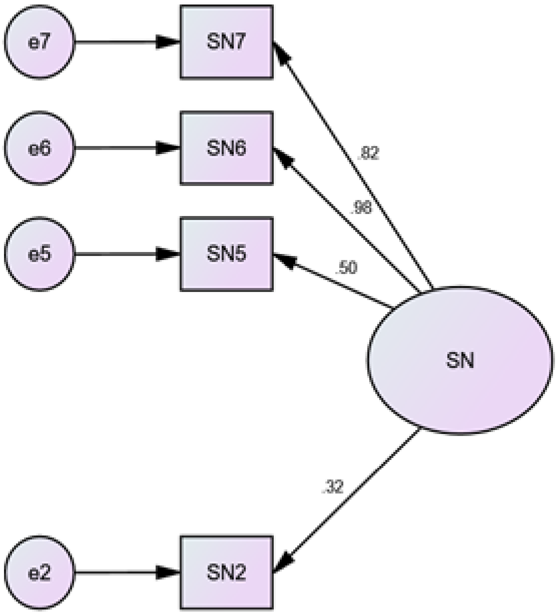


Figure 3.6: Final standardized CFA for SN with 4 items

(**Note**: SN = Subjective Norm)

3.4.7 Confirmatory Factor Analysis for Long Term Orientation

The measurement scale for Long Term Orientation (LTO) consists of 5 items. All 5 items were considered as one factor and entered into CFA analysis process. First, the measurement model should display a good model fit and should satisfy the criteria for various fit indices as explained earlier. The initial measurement model (CFA1) for Long Term Orientation (X^2 = 46.580, *p*-value = 0.000, X^2/df = 9.316**,** GFI = .956, TLI = .850**,** CFI = .925, RMSEA = .144) did not provide an adequate model fit for the empirical data.

Table 3. 8: Fit indices result for LTO

Model	Model Fit Indices						Items deleted	Reason for deletion
	χ2/df	*p*	GFI	TLI	CFI	RMSEA		
CFA1	9.316	.000	.956	.850	.925	.144	-	-
CFA2	6.803	.000	.975	.895	.958	.120	-	-
CFA3	3.923	.008	.989	.947	.984	.080	-	-

The model chi-square was 46.580 with p-value = .000. The normed chi-square (χ^2/df) value for CFA1 showed 9.316, which was higher than the desired cut-off value of 3.0 (Hair et al., 2006). RMSEA value was .144, which was higher than the cut-off value of .08. The GFI value was .956, TLI was .850, and CFI was .925. The GFI, CFI and TLI values should be higher than the recommended level of 0.9. The TLI values did not satisfy the recommended criteria, thus showing inadequate model fit for further analysis. Thus, it was clear that some modifications were required to achieve a model that would better fit with the data.

A review of the MIs for the regression weights (factor loadings) revealed evidence of misspecification associated with items LTO2, LTO3 and LTO5. Considering the modification indices, two rounds of CFA (CFA1 and CFA2) were performed by drawing covariance between the error terms of LTO5 and LTO3 (e5 ←→e3) as well as LTO5 and LTO2 (e5 ←→e2).

After these modifications, the fit indices for the final CFA model (CFA3) improved greatly (X^2 = 11.769, *p*-value = .008, X^2/df = 3.923, GFI = .989, TLI = .947**,** CFI = .984, RMSEA = .080). The revised measurement model is illustrated in Figure 3.7. The chi-square value was 11.769 with p-value = .008. The chi-square normalized by degrees of freedom (X^2/df) also showed an acceptable ratio of 3.923, which was less than the cut-off value of 5. The three fit indices for GFI, TLI and CFI were substantially higher than the .90 threshold for acceptability. Lastly, RMSEA value was found to be .080 which within the cut-off value of .08 for a good model fit.

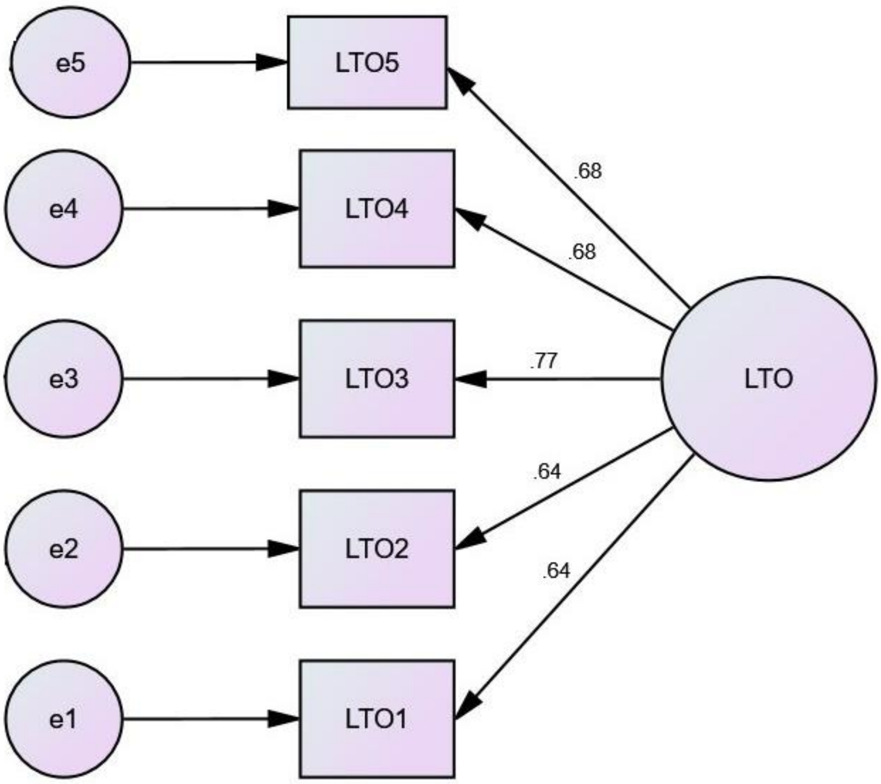


Figure 3. 7: Final standardized CFA for LTO with 5 items

(**Note**: LTO = Long Term Orientation)

3.4.8 Confirmatory Factor Analysis for Financial Risk

The measurement scale for Financial Risk (FIR) consists of 4 items. All 4 items were considered as one factor and entered into CFA analysis process. First, the measurement model should display a good model fit and should satisfy the criteria for various fit indices as explained earlier. The initial measurement model (CFA1) for Financial Risk (X^2 = 79.689, *p*-value = .000, X^2/df = 39.844**,** GFI = .904, TLI = .725**,** CFI = .908, RMSEA = .310**)** did not provide an adequate model fit for the empirical data.

Table 3.9: Fit indices result for FIR

Model	Model Fit Indices						Items deleted	Remarks
	χ2/df	*p*	GFI	TLI	CFI	RMSEA		
CFA1	39.844	.000	.904	.725	.908	.310	-	-
CFA2	1.863	.172	.998	.994	.999	.046	-	-

The model chi-square was 79.689 with p-value = .000. The normed chi-square (χ^2/df) value for CFA1 showed 39.844, which was higher than the desired cut-off value of 3.0 (Hair et al., 2006). RMSEA value was .310, which was higher than the cut-off value of .08. The GFI value was .904, TLI was .725 and CFI was .908. The GFI, CFI and TLI values should be higher than the recommended level of 0.9. The TLI values did not satisfy the recommended criteria, thus showing inadequate model fit for further analysis. Thus, it was clear that some modifications were required to achieve a model that would better fit with the data.

A review of the MIs for the regression weights (factor loadings) revealed evidence of misspecification associated with items FIR1 and FIR2. Considering the modification indices, a covariance was drawn between the error terms of FIR1 and FIR2 (e1 ←→e2). This resulted in an adequate fitting model (CFA2) as shown in Table 3.9.

After these modifications, the fit indices for the final CFA model (CFA2) improved greatly (X^2 = 1.863, *p*-value = .172, X^2/df = 1.863, GFI = .998, TLI = .994, CFI = .999, RMSEA = .046). The revised measurement model is illustrated in Figure 3.8. The chi-square value was 1.863 with insignificant p-value (p = .172). The chi-square normalized by degrees of freedom (X^2/df) also showed an acceptable ratio of 1.863, which was less than the cut-off value of 3. The three fit indices for GFI, TLI and CFI were substantially higher than the .90 threshold for acceptability. Lastly, RMSEA value was found to be .046 which was less than the cut-off value of .06 for a good model fit.

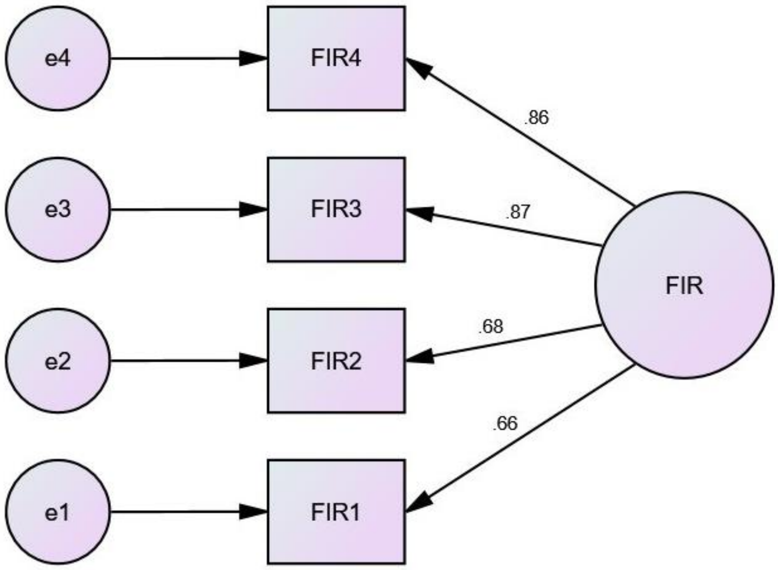


Figure 3. 8: Final standardized CFA for FIR with 4 items

(**Note**: FIR =Financial Risk)

3.4.9 Confirmatory Factor Analysis for Performance Risk

The measurement scale for Performance Risk (PER) consists of 4 items. All 4 items were considered as one factor and entered into CFA analysis process. The results of the initial estimation of the proposed model were acceptable for a well-fitting model.

Table 3. 10: Fit indices result for PER

Model	Model Fit Indices						Items deleted	Reason for deletion
	$\chi 2$/df	*p*	GFI	TLI	CFI	RMSEA		
CFA1	1.988	.137	.995	.983	.994	.050	-	-

The initial measurement model (CFA1) for WPP (X^2 = 3.976, *p*-value = .137, X^2/df = 1.988, GFI = .995, TLI = .983, CFI = .994, RMSEA = .050) provided an adequate model fit for the empirical data. The measurement model is illustrated in Figure 3.9. The standardized loading estimate of the item PER2 was .30, which was less than 0.4. However, it was decided to not delete PER2 and to give additional attention to the item during further analysis as there were no other associated problems. The chi-square value was 3.976 with insignificant p-value (p = .137). The chi-square normalized by degrees of freedom (X^2/df) also showed an acceptable ratio of 1.988. The three fit indices for GFI, TLI and CFI were substantially higher than the .90 threshold for acceptability. Lastly, RMSEA value was also found to be less than the cut-off value of .08 for a good model fit. Thus, the finalized measurement model fit the data well.

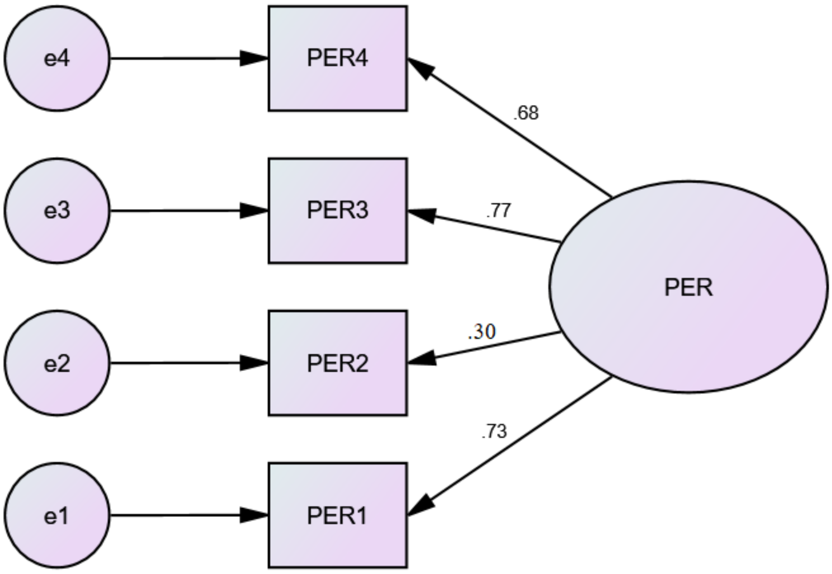


Figure 3. 9: Final standardized CFA for PER with 4 items

(**Note**: PER =Performance Risk)

3.4.10 Confirmatory Factor Analysis for Perceived Behavioural Control

The measurement scale for Perceived Behavioural Control (PBC) consists of 6 items. All the 6 items were considered as one factor and entered into CFA analysis process. First, the measurement model should display a good model fit and should satisfy the criteria for various fit indices as explained earlier. The initial measurement model (CFA1) for Perceived Behavioural Control (χ^2 = 68.737, *p*-value = .000, χ^2/df = 7.637, GFI = .945, TLI = .833, CFI = .900, RMSEA = .128) did not provide an adequate model fit for the empirical data.

Table 3. 11: Fit indices result for PBC

Model	Model Fit Indices						Items deleted	Reason for deletion
	χ2/df	*p*	GFI	TLI	CFI	RMSEA		
CFA1	7.637	.000	.945	.833	.900	.128	PBC6	LFL
CFA2	12.974	.000	.937	.797	.899	.172	PBC4	LMI
CFA3	.126	.882	1.000	1.000	1.000	.000	-	-

Note: LFL = Low Factor Loading; LMI = Large Modification Index

The model chi-square was 68.737 with p-value = .000. The normed chi-square (χ^2/df) value for CFA1 showed 7.637, which was higher than the desired cut-off value of 3.0 (Hair et al., 2006). The GFI value was .945, CFI was .900, and TLI was .833. The GFI, CFI and TLI values should be higher than the recommended level of 0.9. The TLI values did not satisfy the recommended criteria, thus showing inadequate model fit for further analysis. Thus, it was clear that some modifications were required to achieve a model that would better fit with the data.

Firstly, the standardized loading estimate for the item PBC6 was found to be .146, which was far lower than the minimum desired value of 0.5 (Hair et al., 2006). Hence, PBC6 was excluded from the further analysis based on its low standardized loading estimate. Next, MI associated with each constrained path was considered. A review of the MIs for the regression weights (factor loadings) of PBC4 revealed a cross-loading with MI = 12.539. Thus, PBC4 was removed from further analysis.

After these modifications, the fit indices for the final CFA model (CFA3) improved (X^2 = .251, *p*-value = .882, X^2/df = .126, GFI = 1.000, TLI = 1.000, CFI = 1.000, RMSEA = .000). The revised measurement model fit the data well (Figure 3.10). The chi-square value was .251 with insignificant p-value (p=.882). The chi-square normalized by degrees of freedom (X^2/df) also showed an acceptable ratio of .126. The three fit indices for GFI, TLI and CFI were substantially higher than the .90 threshold for acceptability. Lastly, RMSEA value was also found to be less than the cut-off value of .06 for a good model fit.

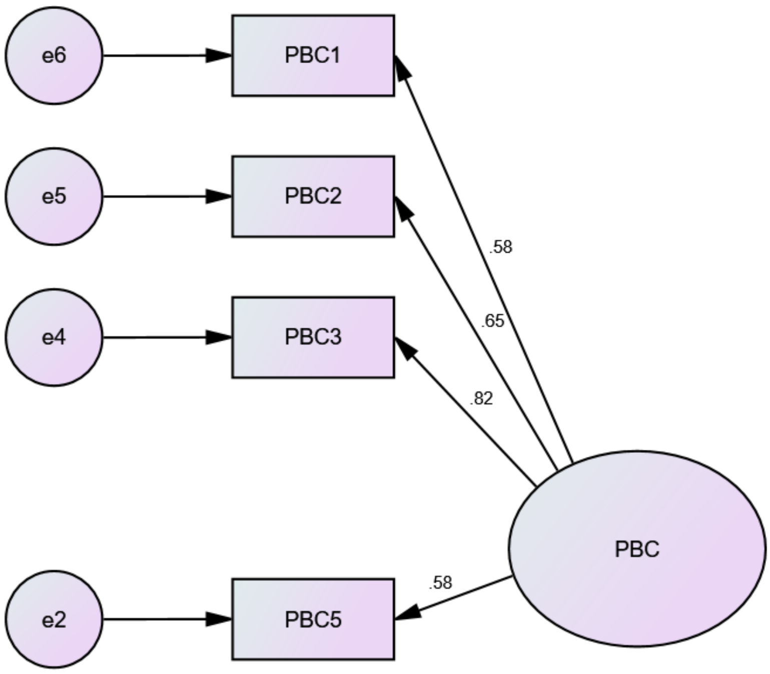


Figure 3. 10: Final standardized CFA for PBC with 4 items

(**Note**: PBC = Perceived Behavioural Control)

3.4.11 Confirmatory Factor Analysis for Adoption Intention

The measurement scale for Adoption Intention (AI) consists of 5 items. All the 5 items were considered as one factor and entered into CFA analysis process. First, the measurement model should display good model fit and should satisfy the criteria for various fit indices as explained earlier. The initial measurement model (CFA1) for Adoption Intention (X^2 = 172.638, *p*-value = .000, X^2/df = 34.528, GFI = .870, TLI = .526, CFI = .763, RMSEA = .288) did not provide an adequate model fit for the empirical data.

Table 3. 12: Fit indices result for AI

Model	Model Fit Indices						Items deleted	Reason for deletion
	χ2/df	*p*	GFI	TLI	CFI	RMSEA		
CFA1	34.528	.000	.870	.526	.763	.288	AI1	LFL, LMI, HSR
CFA2	8.846	.000	.979	.914	.971	.140	AI5	LFL, LMI
CFA3	-	-	1.000	-	1.000	.652	-	-

Note: LFL = Low Factor Loading; LMI = Large Modification Index; HSR = High Standardized Residual

The model chi-square was 172.638 with p-value = .000. The normed chi-square (χ^2/df) value for CFA1 showed 34.528, which was higher than the desired cut-off value of 3.0 (Hair et al., 2006). RMSEA value was .288, which was higher than the cut-off value of .08. The GFI value was .870, TLI was .526, and CFI was .763. The GFI, CFI and TLI values did not satisfy the recommended criteria as the values were lower than the recommended level of 0.9. Thus, it was clear that some modifications were needed to obtain a model that shows adequate model fit for further analysis.

Firstly, the standardized loading estimates for the items AI1 and AI5 were .184 and .231, respectively. These values were far lower than the minimum desired value of 0.5. Secondly, the standardized residuals for the dataset were assessed to identify potential model respecification. The standardized residual between AI1 and AI5 was 10.749, which was higher than the cut-off value of 4. This suggests that covariance estimates of AI1 and AI5 could be more accurate. Theoretically, the items “I intend to purchase green products in the near future” and “I would like to use environmentally sustainable product” seemed to be more closely related. Thus, it was decided to further look at the items AI1 and AI5 to check for other potential problems associated with these items. Moreover, a review of the MIs for the regression weights (factor loadings) revealed that item AI5 have misspecification related with item AI4. Thus, two rounds of CFA (CFA1 to CFA2) were performed by removing the items, AI1 and AI5, based on problems associated with standardised loading estimates, standardised residuals and modification indices.

The revised measurement model consisted of 3 items, as illustrated in Figure 3.11. According to Hair et al. (2018), the models with three items are considered to have a perfect fit by definition. Thus, the resulting GFI, CFI values would be 1.00 and $\chi 2$ value would be 0 according to Hair et al. (2018). As expected, the fit indices for the final CFA model (CFA3) were $\chi 2$ = 0.000, GFI = 1.000**,** CFI = 1.000 and RMSEA = .652. The standardised loading estimates of all items in the final measurement model were higher than the more stringent cut-off value of 0.7. There were no other associated problems with the variable AI, and it was decided to give additional attention to the variable AI during the overall CFA and further analysis as suggested by Hair et al. (2018).

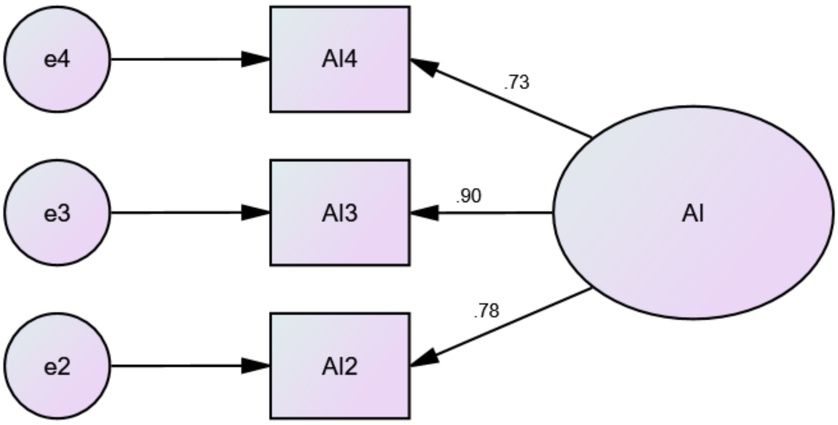


Figure 3.11: Final standardized CFA for AI with 3 items

(**Note**: AI = Adoption Intention)

3.4.12 Confirmatory Factor Analysis for Financial Incentives

The measurement scale for Financial Incentives (FIN) consists of 3 items. All the 3 items were considered as one factor and entered into CFA analysis process. The results of the initial estimation of the proposed model were acceptable for a well-fitting model according to Hair et al. (2018).

Table 3. 13: Fit indices result for FIN

Model	Model Fit Indices						Items deleted	Reason for deletion
	$\chi2$/df	*p*	GFI	TLI	CFI	RMSEA		
CFA1	-	-	1.000	-	1.000	.656	-	-

The measurement model consisted of 3 items as illustrated in Figure 3.12. According to Hair et al. (2018), the models with three items are considered to have a perfect fit by definition. Thus, the resulting GFI, CFI values would be 1.00 and $\chi2$ value would be 0 according to Hair et al. (2018). As expected, the fit indices for the final CFA model (CFA3) were $\chi2$ = 0.000, GFI = 1.000**,** CFI = 1.000 and RMSEA = .656. The standardised loading estimates of all items in the final measurement model were higher than 0.7. There were no other associated problems with the variable FIN, and it was decided to give additional attention to the variable FIN during the overall CFA and further analysis as suggested by Hair et al. (2018).

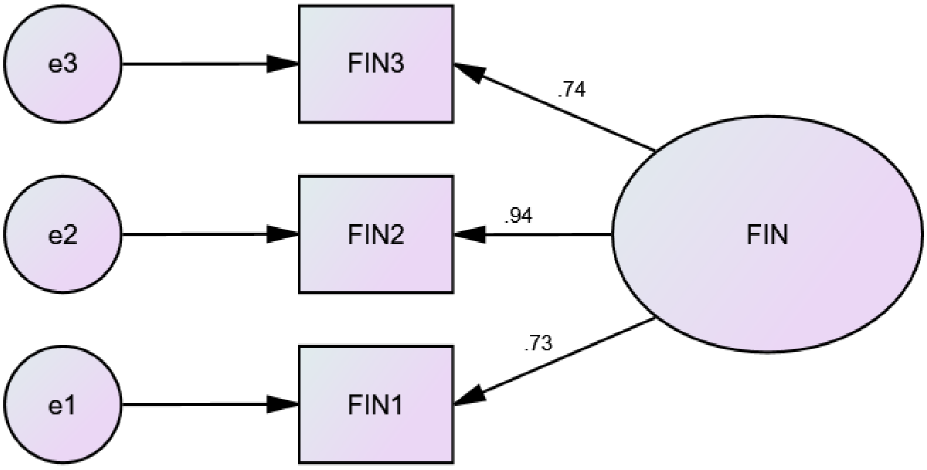


Figure 3. 12: Final standardized CFA for FIN with 3 items

(**Note**: FIN = Financial Incentives)

3.4.13 Assessment of the Overall Measurement Model

The confirmatory factor analysis of individual variables resulted in an overall measurement model which consisted of 52 items. All the 52 items were considered and entered into CFA analysis process. First, the measurement model should display a good model fit and should satisfy the criteria for various fit indices as explained earlier. The initial measurement model (CFA1) for overall measurement model ($\chi2$ = 2363.825, *p*-value = .000, $\chi2$/df = 1.963, GFI = .817, TLI = .866, CFI = .879, RMSEA = .049) did not provide an adequate model fit for the empirical data.

Table 3. 14: Fit indices result for the overall measurement model

Model	Model Fit Indices						Items deleted	Reason for deletion/ Remarks
	$\chi2$/df	*p*	GFI	TLI	CFI	RMSEA		
CFA1	1.963	.000	.817	.866	.879	.049	-	-
CFA2	1.719	.000	.842	.900	.911	.042	PER2	LFL
CFA3	1.579	.000	.902	.921	.930	.038	-	-

Note: LFL = Low Factor Loading

The model chi-square was 2363.825 with p-value = .000. The normed chi-square (χ^2/df) value for the initial model (CFA1) was 1.963, which was within the desired cut-off value of 3.0 (Hair et al., 2006). RMSEA value was .049, which was also within the cut-off value of .06. The GFI value was .817, TLI was .866, and CFI was .879. The GFI, CFI and TLI values did not satisfy the recommended criteria as the values were lower than the recommended level of 0.9. It was clear that some modifications and respecification were needed to obtain a model that show adequate model fit for further analysis. Considering the modification indices, CFA1 was performed in which covariance was drawn between the error terms as shown in figure 3.13.

The resulting second measurement model (CFA2) for overall model (X^2 = 2024.639, *p*-value = .000, X^2/df = 1.719, GFI = .842**,** TLI = .900, CFI = .911, RMSEA = .042) provided a good model fit, except for GFI. CFI value from CFA2 was lower than the recommended value of .90. From further inspection, it was revealed that the standardized loading estimate for item PER2 was 0.336. These values were far lower than the minimum desired value of 0.5. Thus, the item PER2 was removed from further analysis. This resulted in an adequate fitting model (CFA3) as shown in Table 3.14.

After these modifications, the fit indices for the final CFA model (CFA3) improved greatly (X^2 = 1780.856, *p*-value = .000, X^2/df = 1.579, GFI = .902, TLI = .921, CFI = .930, RMSEA = .038). The finalized overall measurement model is illustrated in Figure 3.13. The chi-square value was 1780.856 with p-value = .000. The chi-square normalized by degrees of freedom (X^2/df) also showed an acceptable ratio of 1.579. The three fit indices for GFI, TLI and CFI were higher than the .90 threshold for acceptability. Lastly, RMSEA value was found to be .038, which was less than the cut-off value of .06 for a good model fit.

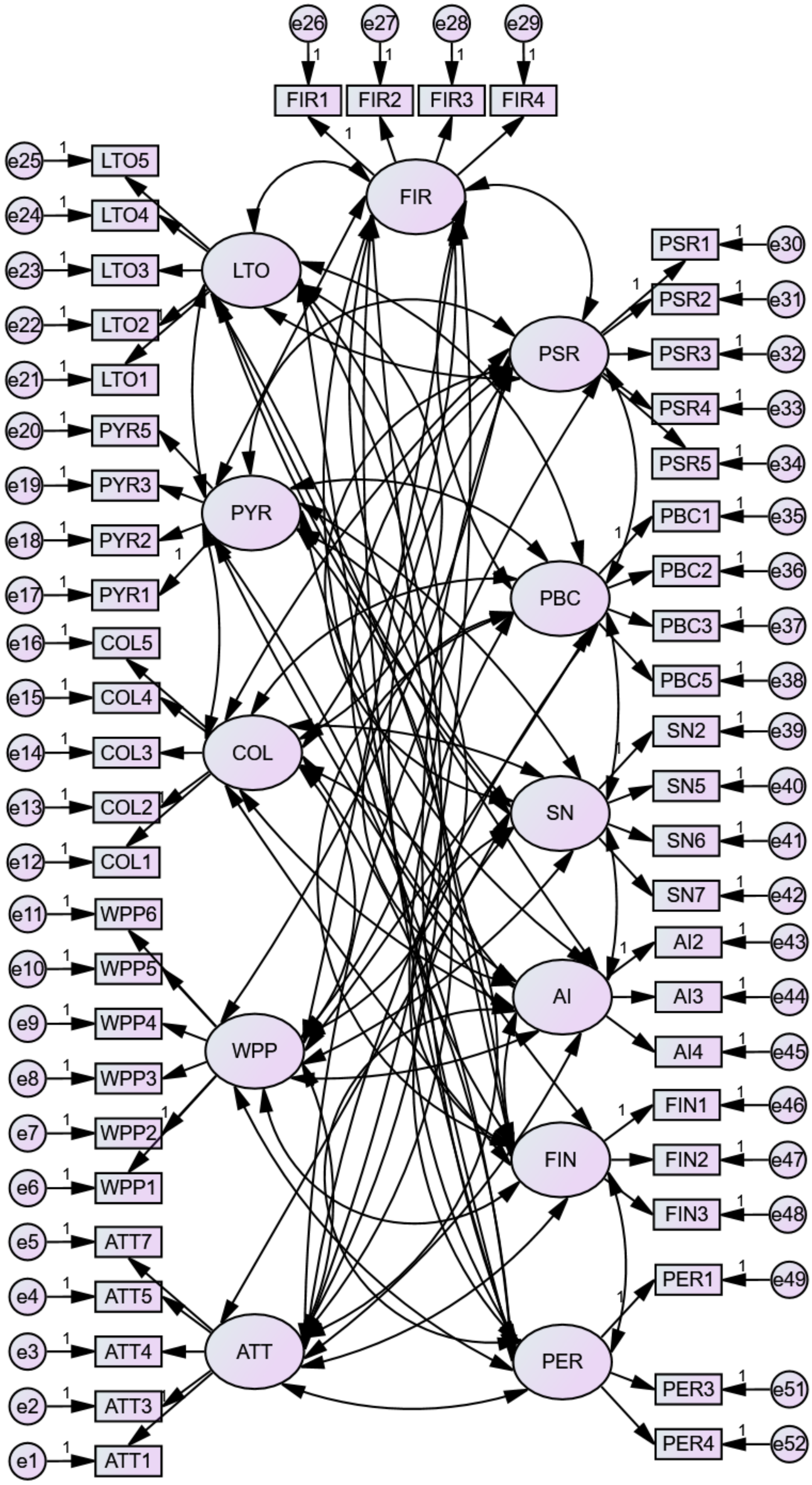


Figure 3.13: Final standardized CFA for overall measurement model with 51 items

3.5 Construct Validity and Reliability

The validation process to ensure construct validity generally involves obtaining a measurement model with good model that meets both convergent validity and discriminant validity (Liao, Chen, & Yen, 2007; Straub, 1989). Thus, before structural model testing, the convergent validity, discriminant validity and construct reliability were examined to verify the construct validity and reliability of the model.

3.5.1 Convergent Validity

As the model fit indices assessment was fulfilled, the next step is to test the convergent validity. Convergent validity is tested utilising the factor loadings and squared multiple correlations (also called item reliability). Table 3.15 illustrates the CFA result that includes unstandardised factor loadings, standardised factor loadings, standard error, critical ratio and item reliability for each indicator.

Firstly, the factor loading estimates of each observed indicators were assessed to test convergent validity. To ensure convergent validity, the factor loading of each observed indicator should be greater than a recommended level of 0.5 (Hair et al., 2006) or an acceptable value of 0.4 (Stevens, 1992). In addition, the factor loadings of each indicator should be significantly linked with the latent construct (Hair et al., 2006). In Table 3.15, the CFA results indicated that all the indicators had standardised factor loadings greater than the required value and all the standardised factor loadings were statistically significant. Thus, convergent validity was verified.

Next, the present study also utilised squared multiple correlations to verify the convergent validity. “Squared multiple correlations” or “Item reliability” refers to the value that represents the extent to which the variance of an observed indicator is explained by the underlying construct (Hair et al., 2006). Generally, the squared multiple correlations of indicators should be greater than the stringent cut-off value of 0.4 (Taylor & Todd, 1995). However, it is normal for the squared multiple correlations of some indicators to go below the cut-off value of 0.4. For instance, the squared multiple correlations for new items or newly developed scales may be below 0.4. Thus, Hulland (1999) suggested that the more suitable cut-off value for squared multiple correlations would be .16 or .25. The squared multiple correlations of all the indicators satisfied the required criteria, thus confirming convergent validity.

In summary, the model has significant factor loadings for all estimates (Table 3.15), no cross-loadings, no justified correlated error terms; the measures in the model have acceptable unidimensionality (Anderson & Gerbin, 1988). Thus, the respecified model fulfils the criteria for convergent validity.

Table 3. 15: Indicator loading for the revised overall measurement model

Variables	Items	Standardized factor loadings	Unstandardized factor loadings	S.E.[a]	C.R.[b]	Item reliability
Attitude	ATT1	0.75	1.00	-[c]	-	0.56
	ATT3	0.69	0.83	0.062	13.369	0.48
	ATT4	0.76	0.89	0.066	13.545	0.57
	ATT5	0.77	0.99	0.078	12.692	0.599
	ATT7	0.61	0.75	0.068	11.083	0.373
Willingness to Pay Premium	WPP1	0.73	1.00	-	-	0.538
	WPP2	0.59	0.73	0.066	11.121	0.342
	WPP3	0.74	0.97	0.061	15.935	0.545
	WPP4	0.84	1.02	0.062	16.502	0.711
	WPP5	0.87	1.09	0.065	16.717	0.754
	WPP6	0.79	0.99	0.059	16.619	0.617
Collectivism	COL1	0.63	1.00	-	-	0.392
	COL2	0.40	0.67	0.127	5.269	0.181
	COL3	0.42	0.77	0.131	5.884	0.174
	COL4	0.53	0.95	0.143	6.68	0.276
	COL5	0.82	1.16	0.135	8.591	0.665
Physical Risk	PYR1	0.59	1.00	-	-	0.35
	PYR2	0.83	1.37	0.117	11.675	0.688
	PYR3	0.83	1.33	0.114	11.652	0.68
	PYR5	0.56	0.99	0.118	8.393	0.312
Long-Term Orientation	LTO1	0.62	1.00	-	-	0.382
	LTO2	0.71	1.08	0.106	10.187	0.499
	LTO3	0.73	1.06	0.093	11.447	0.532
	LTO4	0.77	1.23	0.112	10.967	0.592
	LTO5	0.55	1.11	0.119	9.255	0.3
Financial Risk	FIR1	0.66	1.00	-	-	0.435
	FIR2	0.68	1.03	0.063	16.311	0.464
	FIR3	0.87	1.30	0.094	13.886	0.748
	FIR4	0.86	1.30	0.094	13.883	0.746
Psycho-social Risk	PSR1	0.60	1.00	-	-	0.356
	PSR2	0.63	1.16	0.108	10.778	0.391
	PSR3	0.77	1.41	0.131	10.787	0.598
	PSR4	0.79	1.21	0.111	10.847	0.62
	PSR5	0.40	0.72	0.114	6.305	0.173

Perceived Behavioural Control	PBC1	0.42	1.00	-	-	0.175
	PBC2	0.87	1.89	0.241	7.835	0.756
	PBC3	0.62	1.28	0.151	8.489	0.385
	PBC5	0.54	1.27	0.18	7.045	0.294
Subjective Norm	SN2	0.85	1.00	-	-	0.722
	SN5	0.59	0.66	0.085	7.745	0.345
	SN6	0.88	1.19	0.135	8.762	0.766
	SN7	0.91	1.23	0.136	9.034	0.821
Adoption Intention	AI2	0.80	1.00	-	-	0.631
	AI3	0.87	1.03	0.06	16.982	0.752
	AI4	0.75	0.89	0.058	15.313	0.568
Financial Incentives	FIN1	0.84	1.00	-	-	0.712
	FIN2	0.80	0.87	0.071	12.226	0.633
	FIN3	0.89	0.91	0.061	14.822	0.784
Performance Risk	PER1	0.60	1.00	-	-	0.364
	PER3	0.64	1.28	0.108	11.839	0.414
	PER4	0.82	1.27	0.121	10.533	0.67

Note: [a] S.E stands for Standard Error and is an estimate of the standard error of the covariance; [b] C.R (Critical Ratio) is the critical ratio calculated by dividing the estimate of the covariance by its standard error. A value greater than 1.96 indicate significance level of 0.05; [c] Some critical ratios were not calculated as loading was set to 1 to fix construct variance.

3.5.2 Reliability

The scales for all constructs should be statistically reliable. In addition to factor loadings and item reliability criteria, the convergent validity assessment also includes the measure of construct reliability. Construct reliability should be higher than 0.7 (Nunnally, 1978).

The current study utilised Cronbach's α and Composite Reliability as measures of construct reliability. Table 3.16 illustrates the values of Cronbach's α. Similarly, the composite reliability values of the constructs in the study were: Attitude (0.88), Willingness to Pay Premium (0.91), Collectivism (0.72), Physical Risk (0.80), Long Term Orientation (0.81), Financial Risk (0.90), Psychosocial Risk (0.78), Perceived Behavioural Control (0.80), Subjective Norm (0.79), Adoption Intention (0.85), Financial Incentives (0.88) and Performance Risk (0.81). The construct reliability values (Cronbach's α and Composite reliability) of all constructs were higher than the recommended level of 0.7. Thus, the findings indicated good reliabilities among the indicators used to measure the constructs, and thus construct reliability was achieved. Taken together, the evidence of construct reliability supported the convergent validity of the measurement model.

Table 3.16: Construct Reliability

Variable	No. of Items	Cronbach's α
Attitude (ATT)	5	0.86
Willingness to Pay Premium (WPP)	6	0.89
Physical Risk (PYR)	4	0.77
Long Term Orientation (LTO)	5	0.78
Financial Risk (FIR)	4	0.87
Psychosocial Risk (PSR)	5	0.77
Perceived Behavioural Control (PBC)	4	0.75
Subjective Norm (SN)	4	0.76
Adoption Intention (AI)	3	0.84
Financial Incentives (FIN)	3	0.84
Performance Risk (PER)	3	0.77
Collectivism (COL)	5	0.70

3.5.3 Discriminant Validity

Discriminant validity ensures that the constructs of the model are distinct from one another. In other words, discriminant validity helps in ensuring that the scale indicators of one particular construct are distinctly different from the scale indicators of another construct in the model.

The present study utilised Factor correlation to test discriminant validity as illustrated in Table 3.17 (Bagozzi, Yi, & Phillips, 1991). The result suggests the existence of acceptable distinctiveness between the constructs. For instance, the magnitude of interrelationship among the ‘Physical Risk (PYR)’ and culture construct such as ‘Long Term Orientation (LTO)’ is 0.17 suggesting that the scale items used to measure ‘physical risk’ is distinct from the scale items used to measure ‘long term orientation’. Thus, discriminant validity was verified and confirmed.

Table 3.17: Factor correlation showing degree of interrelationship between the variables

	Variable	1	2	3	4	5	6	7	8	9	10	11	12
1	WPP	*0.89*											
2	ATT	0.50	*0.86*										
3	FIR	-0.16	-0.17	*0.87*									
4	LTO	0.13	0.27	-0.08	*0.78*								
5	PSR	-0.18	-0.29	0.11	-0.24	*0.77*							
6	AI	0.43	0.23	-0.17	0.03	-0.11	*0.84*						
7	PYR	-0.29	-0.32	0.19	-0.17	0.12	-0.21	*0.77*					
8	FIN	0.27	0.26	-0.01	0.20	-0.22	0.08	-0.32	*0.84*				
9	COL	0.18	0.31	-0.01	0.37	-0.16	0.06	-0.25	0.20	*0.70*			
10	PBC	0.40	0.44	-0.22	0.20	-0.11	0.26	-0.31	0.19	0.28	*0.75*		
11	PER	-0.33	-0.35	0.21	-0.25	0.21	-0.18	0.42	-0.33	-0.24	-0.41	*0.77*	
12	SN	0.41	0.35	-0.14	0.13	-0.02	0.29	-0.30	0.21	0.15	0.40	-0.31	*0.76*

Note: The off-diagonal values show Cronbach’s α and are mentioned in italics

Overall, the required reliability and validity assessment supported satisfactory convergent validity and discriminant validity of the measurement model. Hence, the subsequent process of identifying the structural model that best fits the data was carried out to test the relationships hypothesised in the study.

3.6 Common Method Bias

Common method bias might be present as data was collected from the same respondents using the same questionnaire or instrument for both predictor and independent variables (Podsakoff et al., 2003). Harman's single-factor test was followed using SPSS 23.0 to check for common method bias in our study. Harman's single-factor method is an unrotated exploratory factor analysis done on questionnaire. In this test, a single factor should not explain the majority (50% or more) of variance of the questionnaire. In the current study, the single factor extracted could explain only 20.4% of the variance, and hence there is no common method bias issue in the study.

3.7 Structural Model

In the previous sections, the measurement model fit issues, validity and reliability were verified. The following section tests the hypothesised relationship between twelve variables considered in the study. Firstly, the evaluation of theoretical model was carried out based on the same set of fit indices used for the assessment of measurement model in order to ensure a satisfactory Goodness-of-fit to the empirical data (Hu & Bentler, 1999). Then, the magnitude, direction and significance of the path corresponding to each hypothesis in the theoretical model were assessed.

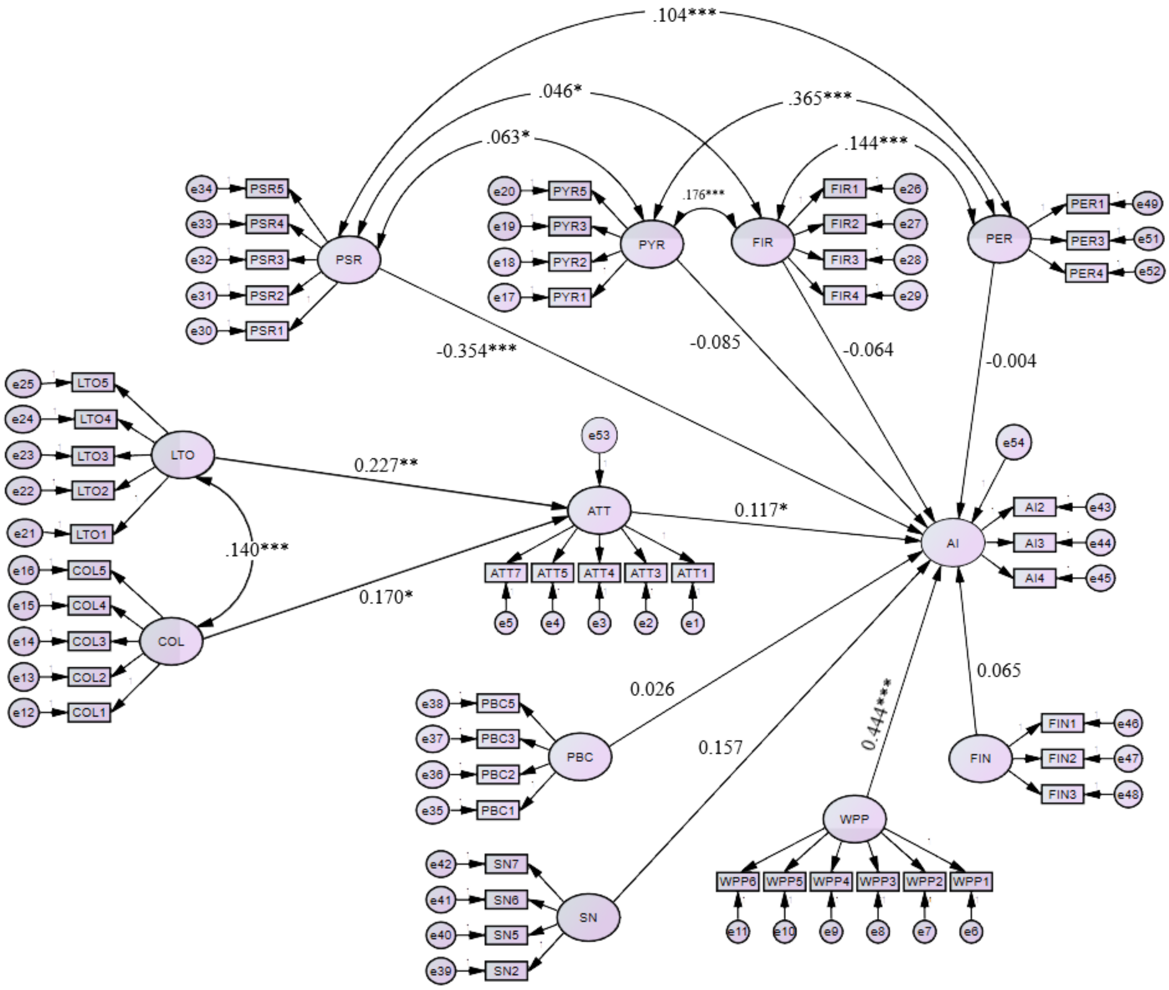
3.8 Evaluation of Hypothesised Model

The Structural Equation Modelling (SEM) technique was the main statistical technique utilised to test the hypothesised relationships in the theoretical model. Initially, the fit indices of the structural model were evaluated. Table 3.18 illustrates the fit measures of the structural model. The fit measures were χ^2/df = 2.305, GFI = .904**,** TLI = .912, CFI = .926, RMSEA = .057 and were found satisfactory.

Table 3.18. Fit measures of the structural model

χ2/df	**GFI**	**TLI**	**CFI**	**RMSEA**
2.305	0.904	0.912	0.926	0.057

The hypothesis testing was carried out as the structural model achieved desired model fit. The significance of each hypothesised path was determined. This was followed by examining the nature and magnitude of the relationships between the variables according to theoretical expectations. AMOS output provides both standardised and unstandardised parameter estimates of all paths, along with test statistics and standard errors for each path. Figure 3.14 illustrates the hypothesised structural relationships between variables and their path estimates.



Note: *** *p*<0.001; ** *p*<0.01; * *p*<0.05; e = error terms.

Figure 3.14: Hypothesised model with standardised path coefficients

The hypotheses were evaluated based on the significance, sign and magnitude of the path coefficients in the proposed model. The size of the effect of an independent variable on its outcome variable could be analysed by examining the absolute magnitude of the respective standardised path coefficients (Hair et al., 2006). The size of the effect of standardised path coefficients for the current study were interpreted based on Kline's (2005) recommendations. According to Kline (2005), standardised path coefficients with absolute value less than 0.1 could be considered as a small effect, with absolute value around 0.30 could be considered as a medium effect and with value greater than 0.5 could be considered as a large effect. The relationships between constructs were also assessed based on the critical ratio (c.r.) value or t-value of the path coefficients between variables. The following sections review each of the hypotheses based on the findings and then summarises the results of hypotheses testing.

3.8.1 The Effects of Theory of Planned Behaviour Elements on Adoption Intention

As discussed before, the elements of Theory of Planned Behaviour (TPB) are Attitude towards electric cars (ATT), Subjective Norm (SN) and Perceived Behavioural Control (PBC). ATT was found to have a positive significant effect on adoption intention (β=0.117, $p < 0.05$). However, SN (β=0.157, $p > 0.05$) and PBC (β=0.026, $p > 0.05$) were found to have insignificant positive effect on adoption intention. Hence, hypothesis H_1 was supported while H_2 and H_3 were not supported as shown in table 3.19.

Table 3.19: Hypotheses testing - The effects of TPB elements on AI

Hypothesised paths			Direction	Beta (β) Estimate	C.R.	Decision
H_1 : AI	←	ATT	+	0.117*	2.252	Supported
H_2 : AI	←	SN	+	0.157	1.135	Refuted
H_3 : AI	←	PBC	+	0.026	0.327	Refuted

Note: β = standardized regression weights; * p<0.05

3.8.2 The Effects of Perceived Risk Dimensions on Adoption Intention

The dimensions of perceived risk discussed in the study are Performance Risk (PER), Financial Risk (FIR), Physical Risk (PYR) and Psycho-social Risk (PSR). PER (β = -0.004, $p > 0.05$) had negative insignificant effect on adoption intention. Similarly, FIR (β = -0.064, $p > 0.05$) and PYR (β = -0.085, $p > 0.05$) were also found to have insignificant negative effect on AI. However, PSR (β=-0.354, $p < 0.001$) had significant negative effect on AI. Thus, Hypotheses H_4, H_5, H_6 were rejected while only H_7 was supported as illustrated in Table 3.20.

Table 3.20: Hypotheses testing - The effects of PER, FIR, PYR and PSR on AI

Hypothesised paths			Direction	Beta (β) Estimate	C.R.	Decision
H_4 : AI	←	PER	-	-0.004	-0.05	Refuted
H_5 : AI	←	FIR	-	-0.064	-1.213	Refuted
H_6 : AI	←	PYR	-	-0.085	-1.193	Refuted
H_7 : AI	←	PSR	-	-0.354***	-5.781	Supported

Note: β = standardized regression weights; *** p<0.001

3.8.3 The Effects of Willingness to Pay Premium (WPP) and Financial Incentives (FIN) on Adoption Intention

WPP (β=0.444, p<0.001) had significant positive influence on adoption intention (AI). FIN had insignificant positive effect on AI (β=0.065, p>0.05). Thus, H_8 was supported and H_9 was not supported. It is shown in Table 3.21.

Table 3.21: Hypothesis testing - The effect of WPP and FI on AI

Hypothesised paths			Direction	Beta (β) Estimate	C.R.	Decision
H_8 : AI	←	WPP	+	0.444***	7.417	Supported
H9 : AI	←	FIN	+	0.065	1.195	Refuted

Note: β = standardized regression weights; *** p<0.001

Interestingly, Willingness to Pay Premium (WPP) was found to be the strongest predictor of adoption intention (AI), followed by Psycho-social risk (PSR). The summary of the results of hypothesis testing is illustrated in Table 3.22. The results of hypothesis testing were further verified by calculating the 95% confidence interval using Bootstrap technique. The 95% confidence interval should not contain zero for the hypothesised relationship to be significant. The 95% confidence interval for the hypothesised relationships were: H_1 [0.025, 0.268], H_2 [-0.041, 0.290], H_3 [-0.088, 0.141], H_4 [-0.107, 0.098], H_5 [-0.161, 0.023], H_6 [-0.180, 0.011], H_7 [-0.582, -0.202], H_8 [0.309, 0.557], H_9 [-0.021, 0.152], H_{10} [0.080, 0.284] and H_{11} [0.116, 0.344]. The confidence interval for H_1, H_7, H_8, H_{10} and H_{11} did not contain zero and hence these hypotheses were accepted. However, the confidence interval for other hypotheses contained zero and hence these hypotheses were rejected. Thus, 95% confidence interval further supported the results of hypothesis testing illustrated in Table 3.22.

Table 3.22: Summary of the hypothesised relationships

Hypothesised paths			Beta (β) Estimate	C.R.	Decision
H_1 : AI	←	ATT	0.117*	2.252	Supported
H_2 : AI	←	SN	0.157	1.135	Refuted
H_3 : AI	←	PBC	0.026	0.327	Refuted
H_4 : AI	←	PER	-0.004	-0.05	Refuted
H_5 : AI	←	FIR	-0.064	-1.213	Refuted
H_6 : AI	←	PYR	-0.085	-1.193	Refuted
H_7 : AI	←	PSR	-0.354***	-5.781	Supported
H_8 : AI	←	WPP	0.444***	7.417	Supported
H_9 : AI	←	FIN	0.065	1.195	Refuted
H_{10} : ATT	←	COL	0.170*	2.201	Supported
H_{11} : ATT	←	LTO	0.227**	3.046	Supported

Note: β = standardized regression weights; *** $p<0.001$; ** $p<0.01$; * $p<0.05$

3.9 Mediation Effect

In the figure used for hypothesis testing (Figure 3.14), Attitude towards electric vehicles (ATT) was hypothesised to mediate the effect that Collectivism (COL) and Long-term orientation (LTO) have on Adoption intention (AI). The mediation relationship was tested following the suggestions of Baron and Kenny (1986).

Table 3.23: Direct, Indirect and Total effects

Variable	Outcome Variable						
	Attitude (ATT)			Adoption Intention (AI)			Mediation effect
	Direct	Indirect	Total	Direct	Indirect	Total	
LTO	0.227**	0.00	0.227**	0.165	0.027**	0.192*	Supported
COL	0.170*	0.00	0.170*	0.118	0.020*	0.138*	Supported

Note: *** $p<.001$; ** $p<0.01$; * $p<0.05$

Considering ATT as outcome variable, COL (β=0.170, p<0.05) and LTO (β=0.227, p<0.01) were found to have significant positive influence on ATT. Hence, hypotheses H_{10} and H_{11} were supported as shown in Table 3.22. Next, the mediating role of ATT in the hypothesised relationships was tested as shown in table 3.23.

The findings indicated that LTO had significant indirect effect (β=0.027, p<0.01) and significant total effect (β=0.192, p<0.05) on AI. However, in the mediating relationship, the direct effect of LTO on AI was statistically insignificant (β=0.165, $p>0.05$). All the required conditions recommended by Baron and Kenny (1986) for mediation were fulfilled, and this revealed that the ATT is a mediator in the relationship between LTO and AI.

Similarly, COL was found to have significant indirect effect (β=0.020, $p<0.05$) and significant total effect (β=0.138, $p<0.05$) on AI. However, in the mediating relationship, the direct effect of COL on AI was statistically insignificant (β=0.118, $p>0.05$). Thus, all the conditions for mediation as suggested by Baron and Kenny (1986) were satisfied, and the findings indicated that ATT plays a mediating role in the relationship between COL and AI.

In addition, Sobel test was also carried out to support the mediation results. According to Baron and Kenny (1986), it would be unusual for the effect of indirect effect to reduce to zero from statistical significance, especially in psychological research. Thus, the degree to which this effect was reduced (i.e., change in the regression coefficients) could be considered as an indicator of the potency of a mediator and the statistical significance of this decrement in the predictive power could be assessed. Formulae to carry out the significance test have been provided by Holmbeck (2002), Baron and Kenny (1986) and Sobel (1982, 1988). A z score could be obtained using these formulae, and this z-score can be compared with a priori critical value ($z = 1.645$ when $p<0.05$ and $z = 2.326$ when $p < 0.01$).

Table 3.24: Summary of hypothesised mediation relationships

Hypotheses statements	Decision
H_{12}: The influence of collectivism on adoption intention of EVs is mediated by the attitude towards EVs	Supported
H_{13}: The influence of long-term orientation on adoption intention of EVs is mediated by the attitude towards EVs	Supported

The indirect effects of COL and LTO on AI were verified using the Sobel test. The significance of indirect paths was calculated using Preacher and Leonardelli (2001). The obtained z score for the indirect path of COL was 2.86 with $p < 0.01$. It was greater than the desired cutoff value of 2.326, and hence the indirect effect of COL on AI was found significant. Similarly, the z score obtained for the indirect path of LTO was 3.50 with $p < 0.01$. It was greater than the acceptable cutoff value of 2.326, and hence the indirect effect of LTO on AI was also found significant. Thus, H_{12} and H_{13} were supported. The results of testing the hypothesised mediating relationships are summarised in Table 3.24. Sobel test confirmed the previous findings that ATT act as a mediator in the relationships that COL and LTO have on AI.

3.10 Summary of the Results

Hypotheses 1, 2 and 3 were related to the elements of Theory of Planned Behaviour (TPB) model, which are attitude towards EVs, subjective norm and PBC respectively. The findings revealed that attitude towards EVs was significantly and positively related to adoption intention of EVs ($\beta=0.117$, $p < 0.05$). However, subjective norm ($\beta=0.157$, $p > 0.05$) and PBC ($\beta=0.026$, $p > 0.05$) were not found to be significantly and positively related to adoption intention of EVs. Thus, the results supported the first hypothesis concerning the significant positive relationship between attitude towards EVs and adoption intention of EVs. The results did not support the second hypothesis concerning the significant positive relationship between subjective norm and adoption intention of EVs. Similarly, results did not support third hypothesis concerning the significant positive relationship between PBC and adoption intention of EVs.

Hypotheses 4, 5, 6 and 7 were related to the perceived risk dimensions, namely Performance Risk (PER), Financial Risk (FIR), Physical Risk (PYR) and Psycho-social Risk (PSR). The findings revealed that Performance Risk ($\beta = -0.004$, $p > 0.05$), Financial Risk ($\beta = -0.064$, $p > 0.05$) and Physical Risk ($\beta = -0.085$, $p > 0.05$) were not significantly and negatively related to adoption intention of EVs. However, the findings indicated that Psycho-social Risk ($\beta=-0.354$, $p < 0.001$) was significantly and negatively related to adoption intention of EVs. Thus, the results did not support the fourth hypothesis concerning the significant negative relationship between PER and adoption intention of EVs. The results also did not support the fifth hypothesis concerning the significant negative relationship between FIR and adoption intention of EVs. Similarly, results also did not support the sixth hypothesis concerning the significant negative relationship between PYR and adoption intention of EVs. The results supported the seventh hypothesis concerning the significant negative relationship between PSR and adoption intention of EVs.

Hypothesis 8 was regarding the significant and positive relationship between Willingness to Pay Premium (WPP) and adoption intention of EVs. The findings revealed that WPP was significantly and positively related to adoption intention of EVs ($\beta=0.444$, $p<0.001$). Thus, results supported the eighth hypothesis related to Willingness to Pay Premium (WPP). Hypothesis 9 concerned the significant and positive relationship between Financial Incentives (FIN) and adoption intention of EVs. The findings revealed that FIN was not significantly and positively related to adoption intention of EVs ($\beta=0.065$, $p>0.05$). Thus, results did not support the ninth hypothesis related to Financial Incentives (FIN).

Hypotheses 10 and 11 were related to the cultural dimensions, namely Collectivism (COL) and Long-Term Orientation (LTO). The findings revealed that Collectivism ($\beta=0.170$, $p<0.05$) and Long-Term Orientation ($\beta=0.227$, $p<0.01$) were significantly and positively related to attitude towards EVs. Thus, the results supported the tenth hypothesis concerning the significant positive relationship between Collectivism and attitude towards EVs. Similarly, the results supported the eleventh hypothesis concerning the significant positive relationship between Long-Term Orientation and attitude towards EVs.

Hypotheses 12 and 13 are related to mediating role of attitude in the relationship between cultural dimensions and adoption intention of EVs. As discussed in section 3.8, all the required conditions for mediation recommended by Baron and Kenny (1986) were fulfilled. Thus, the results supported the twelfth hypothesis concerning the mediating role of attitude between collectivism and adoption intention of EVs. Similarly, the results also supported the thirteenth hypothesis concerning the mediating role of attitude between long-term orientation and adoption intention of EVs.

CHAPTER 4

DISCUSSION

This chapter deals with discussion of results, conclusions, limitations and directions for future research followed by contribution of the thesis. Structural equation modelling was carried out to test the relationships between various constructs in the study and the results of the analysis are discussed in the following sections.

4.1 Objective 1: The Elements of Theory of Planned Behaviour – Adoption Intention Relationship

As explained in the previous chapters, the elements of Theory of Planned Behaviour (TPB) model are attitude towards electric cars, subjective norm and Perceived Behavioural Control (PBC). Attitude towards electric cars was found to be significantly associated with adoption intention. This is similar to the findings of Shalender and Sharma (2021) as well as Jaiswal and Kant (2018) in the Indian context. However, subjective norm and PBC were not significantly associated with the adoption intention towards electric vehicles.

The insignificant effect of PBC is similar to the findings of Asadi et al. (2021) and Zhang, Chen, Wu, Zhang, & Song (2018). Electric vehicles and their usage are still unfamiliar to the general public. According to Notani (1998), the effect of PBC on behavioural intention could be insignificant or weak in unfamiliar contexts. Thus, the unfamiliarity towards the EV could be a reason for the insignificant effect of PBC on EV adoption intention. Findings of the current study regarding the insignificant relationship between subjective norm and adoption intention is similar to previous studies by Paul et al. (2016), Tan, Ooi and Goh (2017), Mohiuddin et al. (2018) and Yazdanpanah and Forouzani (2015). Notably, Ajzen (1991) who proposed the original TPB model stated that the impact of SN on behavioural intention could vary from one context to another and personal considerations tends to overshadow the influence of perceived social pressure in many contexts. As an innovative green product, electric cars would take some time to emerge as a social norm and thus subjective norm did not significantly influence consumers' intention to purchase an electric car in the present scenario. This is further supported by Thøgersen and Zhou (2012) as well as Varshneya et al. (2017) who stated that subjective norm does not influence consumer decisions related to the products that are in the early stages of their product life cycle.

Among the three elements of the TPB model, an individual's attitude towards electric vehicle is the prominent factor that influence his/her electric vehicle adoption intention. The findings indicate that consumers show higher intention towards electric cars when they have a favourable evaluation of electric cars. Thus, government and companies should focus on enhancing and shaping a positive consumer attitude towards electric cars in order to increase the acceptance of electric cars among consumers.

4.2 Objective 2: Perceived Risk Facets - Adoption Intention Relationship

The perceived risk facets that were considered in the study were Performance risk, Financial risk, Psychosocial risk and Physical risk. The perceived risk facets may vary with product category and these dimensions are independent to one another (Laroche et al., 2004). Among the perceived risk facets, Psycho-social risk was found to be the most important risk facet and other risk facets does not have a statistically significant relationship with consumer's intention towards EV adoption.

In the present study, PSR was found to have a significant negative effect on consumer EV adoption intention. The findings regarding PSR is in line with the previous studies that found a significant impact of PSR on consumer behaviour (Ortega-Egea & García-de-Frutos, 2021; Pueschel et al., 2017). This indicate that individuals who feel it embarrassing and uncomfortable to use electric car in public would show lower intention to adopt electric cars. Electric cars are socially visible products that could communicate consumers' social and self-image to the society. There is a high chance of the public identifying and associating the consumer with socially visible products, thus making his or her social and self-image vulnerable to public criticism and judgement (Pueschel et al., 2017). For instance, in the context of electric cars, consumers were found to be experiencing a need to minimise embarrassment created by driving electric cars indicating psychosocial risk associated with electric cars (Graham-Rowe et al., 2012). Similarly, recent studies on consumer emotions related to EVs revealed that negative emotions are more than neutral and positive emotions (Shu, Wang, Lin, Jia, & Zhou, 2022). Thus, considering the fact that India is a collectivistic country, this high social visibility of the electric vehicles and the resulting possibility of negative psychosocial emotions (such as embarrassment) could be the potential reason for the significant negative influence of PSR on consumer EV adoption intention.

The current study revealed an insignificant effect of financial risk, performance risk and physical risk on consumer intention towards EVs. The findings of the current study are similar to previous studies on financial risk (Beneke et al., 2012; S. Jiang, 2016; Sun, 2014), performance risk (S. Jiang, 2016; Petschnig et al., 2014; Tran, 2020) and physical risk (Al-Majali, 2020; Beneke et al., 2012; Petschnig et al., 2014). The risk dimensions perceived by consumers may vary with attributes and characteristics of the product (Featherman & Pavlou, 2003). In the adoption of sustainable innovations, Noppers, Keizer, Bolderdijk, and Steg (2014) observed that symbolic attributes (i.e., positive/negative outcomes on one's self-identity and social status) could be more important than instrumental attributes (such as performance, financial aspects etc.). Petschnig et al. (2014) found that consumers perceived the risk dimensions related to alternative fuel vehicles (such as Physical risk, Performance risk) to be less important compared to other characteristics of alternative fuel vehicles. In addition, Previous studies have revealed that consumers have perception that using electric cars could have a negative impact on their image and identity in the society (Graham-Rowe et al., 2012). In other words, consumers using electric cars could have concerns regarding the impressions they give off to others by choosing an electric car and the perceived identities connected with this car choice (King, Burgess, & Harris, 2019). Cars are considered as a status symbol in India and could have an impact on the identity of an individual in the society (Nielsen & Wilhite, 2015; Verma, 2015). Thus, as a status symbol and identity-defining product, consumers might be concerned more about the potential negative impact of electric cars on their social image and self-image than the other potential risk aspects of electric cars (such as performance risk, financial risk, physical risk etc.). This could be the reason for the prominence of psycho-social risk over other risk facets in the present study.

4.3 Objective 3: Willingness to Pay Premium - Adoption Intention Relationship

Willingness to pay premium was the strongest predictor of consumer EV adoption intention and have a significant positive influence on EV adoption intention. The findings of the current study are similar to the previous studies (Cowan & Kinley, 2014; Dwivedi et al., 2022; Ng et al., 2018; Prakash & Pathak, 2017). Green products are generally priced higher than their traditional alternatives. EVs are priced at least 30% higher than the conventional vehicles and Shalender and Yadav (2018) found that high retail price is the most important consumer challenge in EV adoption. The results indicate that the price difference between EVs and conventional petrol/diesel vehicle are important in influencing their purchase decision. Consumers who are willing to pay more for green products show more affinity to adopt such green products and technologies.

Promisingly, EV industry is currently showing their commitment towards reducing the price premium for EVs through technological advancements (for instance by reducing the battery cost etc.). Meanwhile, as Indian consumers are price conscious, efforts have to be taken to increase their willingness to pay premium for electric cars. For instance, it is worth noting that despite the high initial purchase price, the total ownership cost of EVs (which includes running cost, maintenance cost etc.) is relatively lesser than petrol/diesel vehicles (Shalender & Yadav, 2018). The cost advantages of EVs over conventional petrol/diesel vehicles could be emphasised to increase consumers' willingness to pay premium at the time of purchase. Consumers who prioritise environmental conservation over life convenience were found to be willing to pay premium for green products (Shen, 2012). Thus, marketing efforts to stimulate the environmental concern and consciousness of consumers could help in enhancing the willingness to pay premium for electric cars among consumers. Specific to Indian context, Indian consumers who identify eco-friendly features of green products as environmental benefits would be more willing to pay premium for them (Prakash & Pathak, 2017). Thus, the strong positive effect of willingness to pay premium in the current study underlines the importance of recognising and targeting such consumers as EV purchase price is expected to be higher than its conventional alternatives for some more time and these consumers are more likely to show higher willingness to pay premium for electric vehicles.

4.4 Objective 4: Financial Incentives - Adoption Intention Relationship

Financial incentives were found to have an insignificant effect on the adoption intention of electric cars. The findings of the present study are in line with previous studies (Wang et al., 2018, 2021). According to Charag, Fazili, and Bashir (2019), the absence of government support could create uncertainties among consumers regarding a new product (such as electric car) and could change their perception and attitude towards it. Though state governments provide purchase incentives to private car buyers, the central government emphasise more on the electrification of public transportation for masses and the FAME II purchase incentives provided nation-wide are applicable mainly for electric cars used for public transportation and commercial purposes (Government of India, 2019). In addition, these FAME II incentives could not be availed for car models with ex-factory price greater than INR 15 lakhs. Thus, the absence of sufficient purchase incentives for private car buyers could be a reason why financial incentives did not directly influence the electric car adoption intention. As consumers' lack of awareness regarding government schemes and incentives could have a direct effect on EV adoption (Goel, Sharma, & Rathore, 2021), lack of awareness could be another reason for the insignificant effect of financial incentives on adoption intention. Similarly, considering the high purchase price of electric cars, the low level of satisfaction among potential consumers with the available financial incentives could be another potential reason as suggested by Wang et al. (2021). Thus, it is really important to ensure satisfaction and to reduce uncertainties as well as inconsistencies related to financial incentives.

4.5 Objective 5: Cultural Dimensions and Mediating Role of Attitude

The cultural dimensions considered in the current study were Collectivism and Long-Term Orientation. Collectivism and LTO were found to have a significant positive effect on attitude towards electric cars. The collectivism and LTO did not show significant direct effect on adoption intention. Instead, collectivism and LTO showed significant indirect effect on consumer intention through attitude. Thus, the current study revealed that attitude completely mediates the relationship between the cultural dimensions and intention towards electric cars.

The findings of the present study are similar to previous studies on collectivism (Chan, 2001; X. Jiang et al., 2020; Leonidou et al., 2010; Nguyen et al., 2017; Sreen et al., 2018) and LTO (Leonidou et al., 2010; Nguyen et al., 2017). In Indian context, Khurana, Kumar, and Sidhpuria (2020) found that attitude could act as a full mediator between intention towards EV and its determinant factors. Values are fundamental guiding principles of individuals and typically influence consumers' behavioural intention indirectly through other psychological variables such as attitude (Jiang et al., 2020; Y. Kim & Choi, 2005). Strong cultural values could result in a more positive evaluation of electric cars, which ultimately leads to higher intention to adopt electric cars.

India is a country with a mix of collectivistic and individualist beliefs. However, consumers show collectivistic traits while considering green purchase choices (Sreen et al., 2018). People with collectivistic beliefs show tendencies to take decisions that would be approved by the society. Also, collectivistic people might prioritise the group's interest over their personal interests and motivations (Jiang, Ding, & Liu, 2019). Thus, high collectivistic values could lead a person to show higher positive attitude towards electric cars as indicated by the results of the current study. In other words, current study indicates that individuals who consider the well-being and welfare of the group more important than their own individual goals would show higher positive attitude towards electric cars.

The green products such as electric cars usually provide environmental benefits in the long-term rather than short-term. The environmental benefits of adopting electric cars might not be readily enjoyed by an individual. Instead, the future generation might be more benefitted by such green purchase decisions of the individual. Person with high LTO values would believe in preserving the environment and maintaining sustainable conditions for future generations (Leonidou et al., 2010). Consumers with long-term orientation traits are able to understand and identify the importance of these long-term benefits of green consumption (Nguyen et al., 2017). Thus, LTO is an important cultural value in influencing green consumer behaviour and the effect of LTO on attitude was found to be significant as hypothesised. This indicates that consumers who prefer long-term planning would show higher positive attitude towards electric cars.

4.6 Implications of the Study

4.6.1 Implications for Practice

- Green products need different marketing strategies compared to ordinary products. Thus, the insights and implications from the present study would help policymakers and marketers to formulate better policies and marketing strategies to increase consumer acceptance of electric cars in developing countries.
- Understanding the willingness to pay premium is important for marketers and policymakers as price is the one of most important barriers against green consumption. As the current study found willingness to pay premium to be the strongest predictor of electric car adoption, steps should be taken to increase consumers' willingness to pay premium for electric cars as well as to reduce the difference between the purchase price of electric vehicles and traditional vehicles. The high cost of batteries is a major reason for the relatively higher purchase price of EVs and this higher purchase price could be reduced drastically if the contribution of battery towards the purchase price is reduced. One way to achieve this is to reduce the cost of battery production through technological advancement and through research on the raw materials and methods used for battery production. But as this may take time, other ways could be followed by the stakeholders in the meantime: i) An interesting way to increase the willingness to pay premium among consumers could be to focus on designing, manufacturing and positioning electric cars as superior performance products rather than only focusing on the environmental aspects and benefits of electric cars. For instance, Tesla have primarily marketed itself as a superior performance car than an eco-friendly car and this have played a great role in the success of electric cars manufactured by Tesla (Rezvani et al., 2015)*;* ii) Policymakers could consider the implementation of Battery swapping method wherein consumers could swap their empty battery with fully charged batteries in the battery swapping stations (similar to petrol/diesel refuelling stations). In this method, the car owners do not need to buy or own their own batteries. This could relieve the

consumers from the high price of batteries and reduce the resultant initial high purchase price of EVs; iii) Companies and marketers could also consider following the new practices in automobile industry like leasing the vehicle rather than selling the vehicles to consumers.

- In the present study, attitude was found to be more important than subjective norm and PBC. Thus, a person's favourable/unfavourable evaluation of electric cars plays a major role in influencing his intention towards electric cars. Thus, marketing communications and other campaigns by various stakeholders should be carried out to improve consumers' attitude towards electric vehicles. The need of such marketing communication is further reinforced by the findings that the effect of cultural dimensions (collectivism and LTO) on adoption intention is fully mediated through attitude. The marketing campaigns that stimulate the cultural values (collectivism and LTO) of consumers could be used to enhance consumers' attitude and thereby their intention towards electric vehicles.
- The perceived risk dimensions such as performance risk, physical risk etc. did not influence the consumers' intention towards electric cars. This indicates that consumers have started to feel more confident about electric vehicle and its usage. However, the study found that psycho-social risk have impact on consumers' intention towards EVs. In other words, consumers are concerned about the potential negative impact that the adoption of EVs could have on their self and social identity. It is worth noting that the identity-defining aspect of cars is important in Indian market as it is considered to be one of the major reasons for the failure of people's car "Nano" in the India even though it was relatively more affordable to the Indian consumers (Nielsen & Wilhite, 2015). Thus, considering the importance of psycho-social risk in consumer electric car adoption, government and marketers should strive to enhance the positive image and identity of electric vehicles among the general public to enhance the mass adoption of EVs among Indian consumers.
- Central government and various state governments are providing different incentives to consumers purchasing electric vehicles. Government should take measures to increase awareness regarding these incentives among public and

potential buyers. This is an important step that could enhance the impact of existing financial incentives on the electric car acceptance.

4.6.2 Implications for Theory

- Theory of planned behaviour (TPB) model is open for expansion and could be added with other relevant constructs (Kinnally & Brinkerhoff, 2011). Thus, the current study considered the TPB model as underlying model and extended the TPB model to propose a theoretical framework to predict the adoption intention towards EVs in India.
- As previous studies have mostly focused on drivers of sustainable consumption, barriers associated with sustainable consumption have not been sufficiently studied (Hüttel, Ziesemer, Peyer, & Balderjahn, 2018; McLeay, Yoganathan, Osburg, & Pandit, 2018; Van Doorn & Verhoef, 2015). Similarly, there is a need to investigate potential risks and problems associated with EVs (Park et al., 2018; Tarei et al., 2021). Thus, the present study has responded to these needs by investigating the influence of various risks associated with EVs on EV adoption among Indian consumers.
- While majority of previous researchers have considered perceived risk as a single construct (Jiang & Zhu, 2018), the present study has considered it as a multi-faceted construct. This helped in developing a better understanding regarding the multi-faceted characteristics of perceived risk and how various perceived risk facets influence consumer behaviour as suggested by Lee (2009), especially in the context of EV adoption.
- Similarly, less research was conducted to study the Willingness to pay premium for green products among consumers from developing countries such as India (van Kempen et al., 2009). Though the influence of Willingness to pay premium may vary from one product category to another (Shen, 2012; Yadav & Pathak, 2017), its influence on Indian consumers' EV adoption intention is underexplored. The present study revealed that it is the most important determinant of EV adoption intention among Indian consumers. Thus, this study calls for further studies in other green behaviour contexts to assess the influence of Willingness to pay premium among developing country consumers, especially

from India.

- Liao et al. (2017) and Coffman et al. (2017) pointed out that there is a lack of consensus on the effectiveness of incentive policies on Electric Vehicles preferences. Similarly, Arribas-Ibar et al. (2021) and Rezvani et al. (2015) called for further research on the effect of financial incentive policies on intention towards EVs. Arribas-Ibar et al. (2021) further pointed out this as a research gap in the literature that needs to be filled. To address these, the current study assessed the influence of financial incentives on EV adoption among Indian consumers. The findings of the current study revealed that financial incentives did not influence their EV adoption intention, and financial incentives might not be a strong motivator for Indian consumers to adopt EVs.
- The mediating relationship between various factors influencing EV adoption intention is mostly overlooked by previous researchers (Kumar & Alok, 2020). By considering attitude as a mediator between values and EV adoption intention, the current study has explored mediating relationships between various factors influencing adoption intention. The present study found that the effect of values (namely, collectivism and LTO) on EV adoption intention is fully mediated through attitude. Thus, the study highlights that attitude plays an important role in translating consumer values to consumer intention and behaviours, especially in a sustainable behaviour context.

4.7 Limitations of the Study and Directions for Future Research

- Considering the lack of studies on the consumer adoption of electric cars, the current study focused on the impact of various factors on the consumer adoption of electric cars. Future studies could be undertaken to assess the influence of these factors on the consumer adoption of products from other subcategories of the electric vehicle industry.
- As the government of India focuses on financial incentives as a major motivator for electric vehicle adoption (NEMMP 2020), this study analysed the effect of financial incentives on electric car adoption. Future research could study the effect of non-financial incentives on EV adoption in the Indian context.

- In the present study, data was collected from individuals who possess driving license. Other types of respondents could also be considered in the future studies.
- The current study was cross-sectional in nature; future studies could be undertaken using longitudinal data.
- The present study has utilised quantitative methods to assess the influence of various social and behavioural factors on consumer electric vehicle adoption. Future studies could employ qualitative methods such as interview method etc.
- The current study has focused on adoption intention considering the low market share of electric cars and the resulting practical infeasibility of measuring actual adoption (Rezvani et al., 2015; Shalender and Sharma, 2021). However, future studies could consider consumer adoption behaviour of electric cars.

4.8 Contribution of the Thesis

4.8.1 Theoretical Contribution

- Although there are studies on general green products, research on specific product categories, such as green vehicles, are relatively less in the literature (Zhang & Dong, 2020). Thus, this study contributes to the literature on consumer behaviour regarding green vehicles.
- Among green vehicles, there is relatively less research done on the consumer adoption of electric cars, and this study contributes to the limited literature on electric car adoption among consumers.
- There are relatively few studies focusing on the willingness to pay premium for electric cars by Indian consumers and this study contributes to the literature on consumers' willingness to pay premium for high-involvement green products such as electric cars in Indian context.
- There exists mixed evidence regarding the effect of financial incentives on consumer adoption of electric vehicles (Coffman, Bernstein & Wee, 2017). The current study contributes to the literature by answering the call for further

research in this direction (Arribas-Ibar, Nylund, & Brem, 2021) by examining the effect of financial incentives on electric car adoption among Indian consumers.

- There are studies that examined the influence of perceived risk as a single construct in EV adoption literature. This study extends the literature by considering various dimensions of perceived risk and their influence on EV adoption intention.
- According to Kumar and Alok (2020), previous studies on consumer EV adoption have focused on the antecedents or consequences, thus largely ignoring the mediating relationship between various factors. Hence, this study contributed to the literature by assessing the mediating relationship between cultural dimensions and electric car adoption intention.
- Developing countries could contribute significantly towards electric vehicle adoption in global level. However, there is relatively less research done on electric vehicles adoption in developing countries such as India compared to developed countries. Thus, along with contributing to general literature on electric vehicle adoption, this study also contributes to the limited literature on electric vehicle adoption in the Indian context.

4.8.2 Practical Contribution

- The findings of the study have significant practical relevance as it reflects the opinion and perception of Indian consumers on various aspects related to electric vehicle adoption.
- As a green product category that is still in its infancy, there exists a dearth of studies on EVs in India and thus the present study provides insights to marketers that would help them develop better marketing strategies for EVs in India.
- Similarly, the current study also contributes towards governments' and other stakeholders' active efforts to promote electric vehicle adoption and increase their market share in the Indian automobile market.
- By emphasising the importance of Willingness to pay premium for EVs, the present study urges the practitioners to take measures to reduce the higher

purchase price of EVs as well as to bring price parity between EVs and conventional vehicles.

- As attitude was found to be an important determinant of EV adoption, the present study highlighted the importance of taking steps for attitude formation and developing a positive attitude towards EVs among consumers. From a practical perspective, such steps are even more important considering the findings of the present study that the influence of cultural values that enhance EV adoption are fully mediated by attitude.
- The present study also points out the importance of reducing psycho-social risk compared to other types of risks related to EVs among consumers. Thus, the insights from the study would be beneficial to practitioners and marketers as this is one of the first few studies to empirically evaluate the importance of various risk dimensions in EV adoption among Indian consumers.
- The current study revealed that government financial incentives did not have a significant effect on consumer EV adoption. This hints towards the increased usage of non-financial incentives and less reliance on financial incentives by governments to promote EV adoption, thus facilitating better utilisation of government financial resources.

4.9 Conclusion

The current study utilised extended Theory of Planned Behaviour (TPB) model to analyse the influence of various social and behavioural factors on EV adoption intention among Indian consumers. The present study followed Structural Equation Modelling (SEM) to analyse the relationship between adoption intention and its predictors. Willingness to pay premium was found to be the strongest predictor of adoption intention. This reveals that higher price is a critical factor in the mass adoption of EVs by Indian consumers. Among the elements of Theory of Planned Behaviour (TPB) model, only attitude exhibited an influence on the adoption intention. Among the perceived risk dimensions, Psycho-social risk was found to have a negative significant effect, whereas the other dimensions did not influence the adoption intention of consumers. Financial incentives did not significantly influence the adoption intention of consumers towards EVs. Along with a direct effect on

Attitude, Collectivism and Long-term orientation were also found to have an indirect effect on consumer adoption intention through attitude. The prominence of willingness to pay premium over other factors in the study underlines the importance of policymakers, marketers and other stakeholders taking steps to reduce the disparity between the purchase price of electric vehicles and traditional vehicles. This could be considered one of the primary steps to improve electric vehicle adoption among Indian consumers.

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K V Ansab & Kumar, S. P (***Accepted***). The Role of Anticipated Guilt in Consumer Adoption of Eco-innovation. *International Journal of Business Innovation and Research*.

K V Ansab & Kumar, S. P (*Under Review - revision*). Influence of Government Financial Incentives on Electric Car Adoption: Empirical evidence from India. South Asian Journal of Business Studies.

Papers presented in Conference

K V Ansab & Kumar, S. P (2019). The Influence of Determinant Factors on the Adoption of Electric Vehicles. Paper presented at Doctoral Conclave 2019, March 08-09, 2019, Malaviya National Institute of Technology (MNIT), Jaipur, India.

K V Ansab & Kumar, S. P (2020). The Factors Influencing Electric Car Adoption among consumers in an Emerging Market Context. Paper presented at Society for Marketing Advances International Conference, November 04-07, 2020, Society for Marketing Advances, USA.

APPENDIX

Questionnaires

Dear Respondent,

I am a research scholar of Marketing and Behavioural Sciences. Presently, I am at the stage of collecting data. For this, I have selected some persons whose views I consider valuable. You are one of them, and therefore, I request you to kindly go through the questionnaires attached herewith and give your responses as per the instructions. The questionnaire consists of three parts, and it will not take more than 15 minutes for you in providing all the responses. Since there is no right or wrong answer for any of the questions, you can express your opinions frankly. I assure you that the views expressed by you will be kept confidential and will be used only for academic purposes.

Note: *Battery Electric Cars are defined as "the cars that derive motive power exclusively from electrical batteries in the car which can be charged with a plug through an electric outlet". The major difference between electric cars and conventional cars is the type of fuel used in them.* ***Conventional cars use either petrol or diesel as fuel while Battery-electric cars use electricity as their only fuel*** *(See the figure below)**.** Some of the battery-electric cars available in the Indian market are* ***Mahindra e2o, Mahindra e2o Plus, Mahindra e-Verito, Hyundai Kona, Tata Tigor EV etc.***

Thanking you for your kind cooperation,

Yours sincerely,

Ansab K V

Research Scholar

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Section A

Note: Please tick [√] in the relevant box:

1. Gender ☐ Male ☐ Female
2. Age (years)

   ☐ 18–25 ☐ 26–35 ☐ 36–45 ☐ 46–55 ☐ Above 55
3. Marital status

   ☐ Single ☐ Married
4. Education level

   ☐ Secondary School (class 9 to 10) ☐ Diploma/10+2

   ☐ Graduation ☐ Post-graduation

   ☐ Doctorate or above
5. Monthly Household income (in Rs.)

   ☐ Up to 50,000 ☐ From 50,001 to 100,000

   ☐ From 100,001 to 150,000 ☐ 150,001 and above
6. Region

   ☐ Urban ☐ Semi-urban ☐ Rural
7. Number of cars in the household

   ☐ 0 ☐ 1 ☐ 2 ☐ 3 or more
8. Number of family members (Family size)

   ☐ 1 member ☐ 2–3 members ☐ 4–5 members

   ☐ More than 5 members
9. Daily distance travelled by car (km)

   ☐ Less than 50 km ☐ 50–100 km

   ☐ 100–200 km ☐ More than 200 km
10. How frequently do you use a car for long trips [a distance of over 200km]?

    ☐ Low frequency (holidays, occasional trips)

    ☐ High frequency ☐ Never
11. How much do you think you know about the benefits of using an Electric car?

    ☐ Completely know the benefits ☐ Somewhat know the benefits

    ☐ Don’t know the benefits

Section B

Instructions

Please read the following statements carefully. Five options ranging from *"Strongly Agree to Strongly Disagree*" are given against each statement. The items below ask your opinion about various aspects of an electric car. Show your level of agreement by putting a tick mark [√] in the appropriate box. Please do not leave any item unmarked.

Sl. No.	Statement	Responses				
		Strongly Agree	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**
WPP1	You would pay extra for an electric car even if the performance were same as the conventional car (petrol/diesel car).					
WPP2	You would pay extra for an electric car even if it had a less-appealing design.					
WPP3	The probability that you will pay extra to buy an electric car is very high.					
WPP4	When you replace any vehicle, you are willing to pay extra to purchase an electric one.					
WPP5	Compared with an ordinary non-green car (petrol/diesel car), you are more willing to pay extra to buy an electric car.					
WPP6	You intend to pay more for an electric car.					
ATT1	I like electric car because it is a wise idea to use it.					
ATT2	I like electric car because it is a pleasant experience to ride.					
ATT3	I like electric car because it is necessary for the society.					
ATT4	I like electric car because it gives a positive message to the society.					
ATT5	I like electric car because it is favourable to environment.					
ATT6	I like electric car because it reduces carbon emission.					
ATT7	It is essential to use electric car in India to reduce the fuel consumption.					
PBC1	I believe I have the ability to purchase an electric car.					
PBC2	If it were entirely up to me, I am confident that I will purchase an electric car.					
PBC3	I see myself as capable of purchasing an electric car in future.					
PBC4	I have resources, time and willingness to purchase an electric car.					
PBC5	There are likely to be plenty of opportunities for me to purchase an electric car.					
PBC6	I feel that purchasing an electric car is not totally within my control.					
SN1	People driving an electric car are making a fool of themselves.					
SN2	Driving an electric car is cool.					
SN3	My friends will find it weird that I'm driving an electric car.					
SN4	My family will raise objections against driving an electric car.					
SN5	People who are important to me will support me when I should drive an electric car.					
SN6	People who are important to me tell me that I should consider driving an electric car.					

Sl. No.	Statement	Responses				
		Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
SN7	People who are important to me try to convince me to drive an electric car.					
AI1	I intend to purchase environment-friendly products in the near future.					
AI2	I would buy an electric car even if the quality is lower than a conventional car.					
AI3	I would buy an electric car even if it is less comfortable.					
AI4	I would buy an electric car even if it has a less-appealing design.					
AI5	I would like to use environmentally sustainable products.					
PSR1	People's opinion of me would be negatively affected if I use an electric car.					
PSR2	It would be embarrassing if someone discovers that I drive an electric car.					
PSR3	I would not feel comfortable having an electric car in public.					
PSR4	I would feel ashamed to have an electric car.					
PSR5	I would like to be sure not to receive negative criticism from people I meet.					
PSR6	I would like to be sure not to receive negative criticism from my family.					
COL1	The well-being of my group members is important for me.					
COL2	Individuals should only pursue their goals after considering the welfare of the group.					
COL3	I work hard for the goals of a group, even if it does not result in personal recognition.					
COL4	Family members should stick together, even if they do not agree.					
COL5	I enjoy sharing items and spending time with my group members.					
COL6	People who are important to me want me to buy environment-friendly products.					
LTO1	I tend to use my money carefully in the present so that I can save it for the future.					
LTO2	Failure does not stop me from trying again and again.					
LTO3	I work hard for success in future.					
LTO4	I would like to be secure in the future and hence I prefer long term planning.					
LTO5	I don’t mind giving up today's fun for success in the future.					
FIN1	Overall, financial incentives by the government help me adopt electric cars.					
FIN2	Purchase subsidies help me adopt electric cars.					
FIN3	Reducing purchase-related taxes helps me adopt electric cars.					
PYR1	There is no major health risk for persons using electric cars.					
PYR2	Electric cars are very safe for passengers.					
PYR3	Using an electric car is not very risky for passengers.					
PYR4	There exists low risk of injury for persons using electric cars.					
PYR5	Electric cars represent a low accident risk for passengers.					

Section C

Instructions

Please read the following statements carefully. Seven options *"Extremely risky to Not at all risky/ Extremely sure to Not at all sure/ Extremely confident to Not at all confident"* are given against each statement. Show your opinion regarding each statement by putting a tick mark [√] in the appropriate box. Please do not leave any item unmarked.

Sl. No.	Statement	Responses				
		Extremely risky	**Very risky**	**Moderately risky**	**Slightly risky**	**Not at all risky**
FIR1	How risky (financially) do you feel it is to purchase an electric car?					
FIR2	Given the uncertainty of electric vehicles, how much is the risk involved in purchasing an electric car?					
FIR3	Considering the amount of money associated with purchasing an electric car, how risky is the purchase?					
FIR4	How much financial risk is involved when purchasing an electric car?					
PER2	Considering the possible problems associated with electric car's performance, how much risk would you say would be involved with purchasing an electric car?					
Sl. No.	**Statement**	**Extremely sure**	**Very sure**	**Moderately sure**	**Slightly sure**	**Not at all sure**
PER1	How sure are you about the electric car's ability to perform satisfactorily?					
PER3	In your opinion, do you feel sure that an electric car would perform as well as a conventional petrol/diesel car now on the market?					
Sl. No.	**Statement**	**Extremely confident**	**Very confident**	**Moderately confident**	**Slightly confident**	**Not at all confident**
PER4	How confident are you of the electric car's ability to perform as expected?					

**** Thank you ****

BIO-DATA

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ACADEMIC QUALIFICATIONS

National Institute of Technology Karnataka (NITK), Surathkal
PhD* (Pursuing)
Title: "Impact of Behavioural and Social Factors on the Intention to Adopt Electric Vehicles: An Empirical Investigation"

UGC
UGC NET and JRF in Management (2016)

University of Calicut, Kerala
Master of Business Administration (Marketing & Human Resource) (2016)

University of Calicut, Kerala
Bachelor of Technology (B. Tech) in Electronics and Communications Engineering (2014)

EXPERIENCE

Suzuki Nexa
Relationship Manager (2016 – 2017)

DDB Mudra Kerala
Marketing Intern (2015 – 2016)

PepsiCo India Private Limited, Kerala
HR Intern (2015 – 2015)

PUBLICATIONS & CONFERENCES

- **K V Ansab** & Kumar, S. P (In press). The Role of Anticipated Guilt in Consumer Adoption of Eco-innovation. *International Journal of Business Innovation and Research*.
- **K V Ansab** & Kumar, S. P (2020). The Factors Influencing Electric Car Adoption among consumers in an Emerging Market Context. *Society for Marketing*

Advances International Conference, November 04-07, 2020, Society for Marketing Advances, USA.

- **K V Ansab** & Kumar, S. P (2019). The Influence of Determinant Factors on the Adoption of Electric Vehicles. *Doctoral Conclave 2019*, March 08-09, 2019, Malaviya National Institute of Technology (MNIT), Jaipur, India.
- **K V Ansab** (2014). Improved Waste Heat Harvesting for Better Energy Conservation. *International Conference on Intelligent Engineering Systems*, April 03-04, 2014. EASA College of Engineering and Technology, Coimbatore, India.
- **K V Ansab** (2014). Thermoelectric Energy Generator for Waste Heat Recovery Using Quantum dot. *National Conference on Latest Advancements in VLSI, Embedded Systems and Signal Processing*, February 21-22, 2014. Ammini College of Engineering, Kerala, India.

PAPER PRESENTATIONS

- *Grid connectivity of Renewable Energy – Issues & Solutions* at Centre for Excellence in Engineering and Business Administration (CEEBA), a forum of KSEB Engineers' Association (KSEBA) supported by IEEE Power & Energy Society Kerala (IEEE-PES Kerala Chapter).
- *Waste Heat Harvesting for Efficient Devices Using Quantum Dots* at BRAHMAVEGA-2013 (National Level Tech Fest) at Royal College, Thrissur and Indian Society for Technical Education (ISTE)
- *Waste Heat Harvesting for Energy Efficient Computers* at PRAYAANA-2013 (South Zone Inter Collegiate Meet)

WORKSHOPS & TRAINING ATTENDED

- Online FDP on *Data Analytics for Business Decision* conducted by Saintgits Institute of Management, Kottayam from 20th to 22nd October 2020.
- *Paper Development* workshop organised by Manel Srinivas Nayak Institute of Management on 11th January 2021.
- JMP academic workshop on *Statistical Discovery for Management Sciences using JMP* organised by School of Management, National Institute of Technology Karnataka (NITK), Surathkal, India held from 10th May 2021 to 14th May 2021.

- Workshop on *Developing and Testing Moderation Models in Management Research* organised by School of Management Studies, University of Hyderabad between 22nd and 23rd August, 2020.
- *ICSSR-Sponsored Ten Days Research Methodology Workshop for Research Scholars in Social Sciences* organised by School of Management Studies, National Institute of Technology Calicut from 11th to 20th March 2019.
- Workshop on *Reviewing and Evaluating Scientific and Management Literature using Bibliometrics* organised by School of Management, National Institute of Technology Karnataka on 19th December 2018.
- Five Days Continuing Education Program on *Computational Intelligence and Statistical Based Data Analytics* organised by School of Management, National Institute of Technology Karnataka from 3rd December 2018 to 7th December 2018.
- Workshop titled *Zero to One: The Fundamentals of Starting Up* conducted at Entrepreneurship Summit NITK on 7th April 2018.
- Workshop titled *Investing in the Present Scenario* conducted at Entrepreneurship Summit NITK on 8th April 2018.
- *Seven Days workshop on SPSS And Research Methodology* organised by Department of Rural Management, Babasaheb Bhimrao Ambedkar University during 13th December 2017 to 20th December 2017.
- In-plant training at *Indian Telephone Industries (ITI) Limited Kerala*, an ISO 9001:2000 and ISO 14001:2004 certified Public Sector Unit.
- Workshop on *Embedded system & Programming* conducted by Malabar Centre for Technical Research (MCTR).
- *SatBot, a robotic workshop* conducted by Technophilia System & Robotics and Computer Application Institute of USA.
- National Level workshop in *Radiochemistry* held at Malabar College of Engineering Technology.

<u>TALKS ATTENDED</u>

- *AI Summit 2021* organised by School of Business & School of Technology, Woxsen University, India.

- *India's First Leadership Talk Series Session with Mr. Mahesh Babu (CEO, Mahindra Electric Mobility Ltd.)* by MHRD's Innovation Cell (Government of India) and AICTE, India.
- Webinar on *Why Academic Journal Publication is important?* on 4th July 2020 organised by PG Department of Commerce, Thiruvalluvar University College of Arts and Science, Tirupattur, India.

CERTIFIED COURSE

- *Two months certificate course in Computer hardware and maintenance* by G-TEC Computer Education Associated with American Central University and ICDL Asia Pacific Limited.

LEADERSHIP EXPERIENCE

- Coordinator (Head) for the TEQIP-III sponsored 6-days workshop titled *Cybersecurity for Business Leaders and Managers* organised by National Institute of Technology Karnataka (NITK), Surathkal.
- Chief-Coordinator of National level workshop on *Decision-Making with MS Excel: A Data-Driven Approach* organised by Department of Commerce and Management Studies, University of Calicut for working professionals.
- Coordinator of Marketing Competition *The Buzz* conducted by University of Calicut.

HONOURS & ACTIVITIES

- Won "*THE GREEN ENGINEER*" competition powered by Microsoft, Mozilla Firefox, Google Student Ambassador, IEEE Advancing Technology for Humanity, IEEE Computer Society, Start-Up Village, SAE India, Greenpeace & Wikipedia.
- Secured 80% in the National Level Commerce Quiz organised by the Department of Commerce, St. Teresa's College (Autonomous), Ernakulam, India.