Print ISSN: 1738-3110 / Online ISSN 2093-7717
JDS website: http://kodisa.jams.or.kr/
http://dx.doi.org/10.15722/jds.18.9.202009.31

A New Product Risk Model for the Electric Vehicle Industry in South Korea*

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Received: July 16, 2020. Revised: July 16, 2020. Accepted: September 05, 2020

Abstract

Purpose: This study examined a comprehensive model for assessing the success probability of electric vehicle (EV) commercialization in the Korean market. The study identified three risks associated with successful commercialization which were technology, social, policy, environmental, and consumer risk. **Research design, methodology:** The assessment of the riskiness was represented by a Bayes belief network, where the probability of success at each stage is conditioned on the outcome of the preceding stage. Probability of success in each stage is either dependent on input (i.e., investment) or external factors (i.e., air quality). Initial input stages were defined as the levels of investment in product R&D, battery technology, production facilities and battery charging facilities. **Results:** Reasonable levels of investment were obtained by expert opinion from industry experts. Also, a survey was carried out with 78 experts consisting of automaker engineers, managers working at EV parts manufacturers, and automobile industry researchers in government think tanks to obtain the conditional probability distributions. **Conclusion:** The output of the model was the likelihood of success – expressed as the probability of market acceptance – that depended on the various input values. A model is a useful tool for understanding the EV industry as a whole and explaining the likely ramifications of different investment levels.

Keywords: Electric vehicle, New product development, Innovation, Bayes belief network, Market risk

JEL Classification Code: M10, M13, R40, R42

1. Introduction

In many automobile-producing nations, electric vehicles (EV) are emerging as the future. As the public becomes more cognizant of the negative environmental impact of internal combustion engine vehicles (ICVs), societies are promoting EVs as a more environmentally friendly technology for transportation.

In Asia, South Korea is emerging as a major manufacturer of EVs. Manufacturers are gearing up their production facilities to produce more EVs in more model variations. Hyundai Motors plans to introduce 44 models of EVs by 2024, with an annual local production of 70,000 EVs (more will be produced globally). Hyundai has plans to invest more than $3 billion dollars in EV production by 2024[1].

* Funding: This work was supported by the Korea Ministry of Education and National Research Foundation (grant number: NRF-2016S1A5A2A03926414)
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The consumer market for EV is still small in Korea, and the Korean government has implemented various policies to boost EV sales. In order to promote EVs, the Korean government has set subsidies up to $11,000 per vehicle. Although only 29,000 EV were sold in 2019, the government has an ambitious plan to supply 430,000 EVs by 2022. Further, to facilitate convenience, the government has installed 35,000 low-speed and 5,000 high-speed chargers, and the government has plans to install an additional 10,000 high-speed chargers by 2022[2].

Signs of a full-fledged EV market also show up in consumer surveys. A study of 177 Korean EV owners shows that 93% of owners were "satisfied" or "very satisfied" with their EV (Chu et al. 2019). This number far exceeds the satisfaction levels of internal combustion vehicles (ICVs). The most satisfying aspect of EV ownership was low maintenance cost: average charging cost of EVs from the survey was a mere 20,000 won per month, which is 1/10 of the fuel consumption of comparable ICVs. Korean owners were also satisfied with the innovativeness of the EV and the fact that it is contributing to better the environment. In terms of range anxiety, the study showed that anticipated anxiety of potential adopters was higher than the actual anxiety experienced. It also appears that operating an EV requires a fair amount of behavioral change on the part of the driver. Insights gained from the study on satisfaction of early adopters of EVs suggest that positive word-of-mouth for EVs will spread rapidly.

But there are also obstacles. The most serious of these is the budgetary limitation on government incentives. The 29,000 EVs sold in 2019 was the limit of the government's budget for incentives. When the total budget ran out, no further incentives could be given, and orders for EVs were halted. At the current level of incentive budget, EV market share cannot exceed 2% of total car sales. In the future, the government will decide whether to increase the budget or reduce the subsidy amount per vehicle.

The next three to five years will be critical for determining the competitiveness of the EV industry for Korea. As such, the government and automakers are making bold bets, in order not to be left behind. However, there are large risks associated with making EVs a commercial success and a systematic assessment of various risk factors need to be considered.

Many of the success factors for developing a strong EV industry are related hierarchically. Namely, we may have a factor, say X, which affects Y, but Y in its turn affects Z. A Bayes belief network (Jensen, 1996) is the appropriate method for analyzing a structure where the variables become interrelated hierarchically through conditional probabilities. In this study, we use an elementary Bayes belief network to combine all the factors affecting EV success into a single conditional probability model.

2. Literature Review

New Product Development (NPD) is an integral aspect of business innovation which is needed for business survival. In the era of shortening product life cycle and discontinuous innovation, NPD is becoming increasingly important (Cooper, 1990; Loch & Kavadias, 2008; Kahn, 2013; Cooper, 2017). NPD is not restricted to the domain of physical products, as services become important and product and service are often sold together as a package. For this reason, some researchers have even paraphrased NPD and New Service Development (NSD) (Crawford, 2011). For this study, the reference to NPD implies products in a broader sense that includes services. The advent of the 4th Industrial Revolution requires businesses to change and adapt to new innovations in technology and business models. However, these requirements and changes are increasing uncertainty for business, and this requires an NPD process that actively manages risk.

Over the last three decades, many research has been conducted in the NPD domain, including NPD process, NPD framework, NPD models, NPD successes and failures, and NPD risk management. Risk management in NPD covers questions regarding ways to avoid, transfer, remove and manage risk in the NPD process (Pinheiro et al., 2019). Based on these considerations, the literature review will cover NPD, and new product risk management (NPRM).

The definition of a new product, in itself, can be quite varied. Loch and Kavadias (2008) defined NPD as a set of business actions which directs new and changed products into the market. The concept of newness can be new-to-the-world, new product lines, additions to existing product lines, line improvements and revisions, repositioning and cost reductions (Cooper, 2017; Kahn, 2013; Trott, 2008). Loch and Kavadias (2008) also commented that NPD has many sub-actions and related actions, and therefore needs to be understood as a set of sub-processes.

2.1. NPD Process/Framework/Model

NPD can be understood as a process, a framework or a model. Among these, many NPD studies have focused on viewing it as a process. According to Booz Allen and Hamilton, NPD process can be broken up into seven steps: new product strategy development, idea generation, evaluation, business analysis, development, testing and commercialization. Similarly, NPD is viewed as a series of stages and gates (Cooper, 2017), where progress in each stage is evaluated at the gates for a go-no-go decision.

While much of NPD research is on the stages of development, Kahn (2013) has extended the scope from just development stages to dimensions and competencies. As mentioned earlier, Loch and Kavadias (2008) viewed NPD as a set of sub-processes consisting of variant generation process, selection process, transformation process, and coordination process. Other extensions of the typical stage-gate model are the emphasis on the uncertainty of the natural, market and technological change, and the role of the team members and leaders in the NPD process. Loch and Kavadias (2008) criticized that many NPD research that just focused on the NPD process as a silo. To broaden the scope, Trott (2008) suggested NPD be expanded to actions that assemble knowledge on the business opportunity, product concept, product prototype, technical testing, and the market. There has also been much research carried out in NPD of high-tech companies (Porananond & Thawesaengskulthai, 2014; Aleixo & Tenera, 2009; Glueck-Chaloupka et al., 2005). Aside from the traditional NPD stages, research in high-tech stresses the importance of feasibility, trial-ability, commercialization, diffusion and local adaptation.

In a review of the NPD process research, Trott (2008) categorized eight different NPD models. The departmental-stage model emphasized the working of each department; the activity-stage model emphasized the cross-departmental collaboration and feedback; the cross-functional model attempted to overcome the limitations in the current organizational structure; the decision-stage model is the traditional stage-gate model; the conversion process model treats every stage as starting from input and producing an output; the response model emphasized the decisions that are made; and the network model incorporates input from outside the organization.

Stressing sustainability, Pinheiro et al. (2019) explained the role of NPD in a circular economy (i.e., a sustainable-regenerative economy) in an era of resource depletion. To date, studies related to NPD process, framework and model have been the foundation of much NPD research. Nevertheless, another important area of research is into the risks associated with NPD, and the reasons for success and failure of NPDs.

2.2. NPD Risk Management

NPD can be viewed as a journey of managing uncertainty, solving issues and mitigating risk (Cooper, 2017). Thus many researchers agree that risk management is one of the important sub-domain in NPD (Loch & Kavadias, 2008; Kahn, 2013; Cooper, 2017). Furthermore, some have asserted that a new product cannot truly be progressive or novel if it does not have a risk. Risk management is essential to any continuing business. Moreover, NPD is viewed as a project rather than an ongoing process. So risk management has been intensively studied in the context of project management. It is somewhat obvious that NPD has the characteristic of the project rather than operation. Many studies of risk management in new products are based on the concepts of project risk management, which are risk identification, risk classification and risk mitigation (Porananond & Thawesaengskulthai, 2014; Ayala-Cruz, 2016; Stosic et al., 2017).

In NPD, it is not possible to avoid risks, so managers should implement a process of reducing risk accruing from the uncertainty of the process. Cooper suggested five rules for reducing risk: (a) when uncertainty is high, keep the stakes low (b) when uncertainty is low, increase the stakes (c) incrementalize the new product process (d) view each stage as a means of reducing uncertainty and (e) make a timely evaluation and get-out points. The Project Management Institute describes project risk management as the process of planning, identification, analysis, monitoring and control.

It is surprising that majority of the studies of new product risk management (NPRM) have focused on "project" or "product" risk management. Out of 23 risk factors, 70% of the variance in performance can be explained by 5 main factors which were predominantly "product" risk. However, there are other risks such as product quality risk, consumer acceptance risk, and regulatory risks and so on. Recent research is being extended to consider all the related factors that affect the success of an NPD project (Porananond & Thawesaengskulthai, 2014). As an example, Bendoly et al. (2012) suggested the establishment of an appropriate information system for risk management. In such a system, project members are required to share risk assessments and solutions to risky situations.

2.3. NPD Risk Category and Factor

Research in NPD risk management is followed by studies on risk categorization and risk factors. Baccarini and Archer (2001) proposed a project risk ranking system for prioritizing risk factors. This ranking system has three steps: risk rating, risk management planning and risk monitoring. In their paper, 17 risk factors in NPD are articulated, in the areas of product quality, financing, medical danger, management and stakeholders. At a micro level, Keizer et al. (2002) identified 142 types of risk in 12 categories. Many research has categorized risk more broadly from 5 to 10 categories. For example, Nielsen (2006) classified risk into operational, technological, financial, procurement, political, environmental, social, and economic. Murray et al. (2011) has nine factors; technological & operational, financial & economic, procurement & contractual, political, environmental, social, regulatory & legal, safety and delay. Meanwhile, Barber (2005) stated that risk can be classified as simply external or internal.

Prior research has studied the relationship between risk and performance and showed that the timing of intervention and the appropriateness of performance measures were important factors for success. Liu and Liu (2013) focused on risk management at the commercialization stage. Oehmen et al. (2014) dealt with the impact of risk-responsive action on NPD performance.

2.4. Industry-Specific NPRM

Over the last three decades, NPRM has been one of the leading research domains in NPD. Based on the consensus that NPD is a risk mitigation process, NPRM has been continuously evolving against the changes in technology, enterprise, industry and the market. Due to rapid change, there has evolved both a general holistic approach as well as specific case and industry studies.

Porananond and Thawesaengskulthai (2014) proposed an NPRM model for the food industry in Thailand and Wahyudin and Santoso (2016) in the food industry in Indonesia. Meanwhile, Kirkire et al. (2015) studied NPRM in the industry of medical device manufacturing and proposed a risk mitigation model consisting of nine technological risks, eight strategic management risks and three market risks. Goswami, (2018) proposed a risk assessment framework for the construction and mining industry. In studying NPRM in the high-tech industry, Ayala-Cruz (2016) argued that the existing PMI model of risk management could not be applied directly, and suggested several modifications to fit the high-tech industry. Zhang et al. (2015) conducted a case study of risk management in China, in the context of customer collaboration.

Kasemset et al. (2014) examined risks in the supply chain, and Bhaskaran and Krishnan (2009) examined risk reduction mechanisms associated with inter-firm collaboration. In particular, the authors' introduction of factors related to network type (e.g. crowdsourcing, joint R&D, R&D contract) was unique. Qazi et al. (2016) specifically focused on the harmful effects of complexity in risk management and proposed ways to control complexity. Stosic et al. (2017) dealt with risk in innovative product development. Stosic et al. (2017) used three risk categories; management, technology, and market. The management category included management methods, IP team, budget, project organization; the technology category included development process, product planning and design; and the market category included government, suppliers, and competitors as risk factors.

Finally, Yadav et al. (2007) carried out of a review of the NPD literature and showed that NPD plays a critical role in the competitiveness of firms. They also showed that NPD in many firms were not adequately updated to meet the requirements of today's global market needs.

2.5. NPD Risk Management Tool & Techniques

In terms of tool and techniques of research, in NPD and NPRM, diverse research methodologies are used depending on the topic addressed. These are Analytic Hierarchy Process, Bayesian belief network, FMEA, Fuzzy set, Expected utility theory, Game theory, Monte Carlo Simulation, Bubble Diagrams, House of Risk, Risk Breakdown Structure and Control Charts (Porananond & Thawesaengskulthai, 2014).

3. Risk Factors Affecting EV Success

There are many types of risks in making EVs a commercial success. Commercial success is ultimately the market acceptance of the product at a given price. As more consumers decide to choose an EV over a comparable ICV, the probability of commercial success should increase. In this study, it is presumed that the manufacturer is offering the EV at a price that guarantees a certain return on investment. Also, the analysis of risk is taken from the perspective of a business that is investing in EV technology. Businesses are not limited to automakers, but also includes battery manufacturers, parts manufacturers, charging facility operators, and any other business in the EV value chain. The types of risks identified from the prior literature and field research were as follows: technological risk, environmental-social-policy risk and consumer risk. These risk factors are interrelated to one another hierarchically, forming an industry ecology surrounding EVs. The conceptual model is outlined in Figure 1.

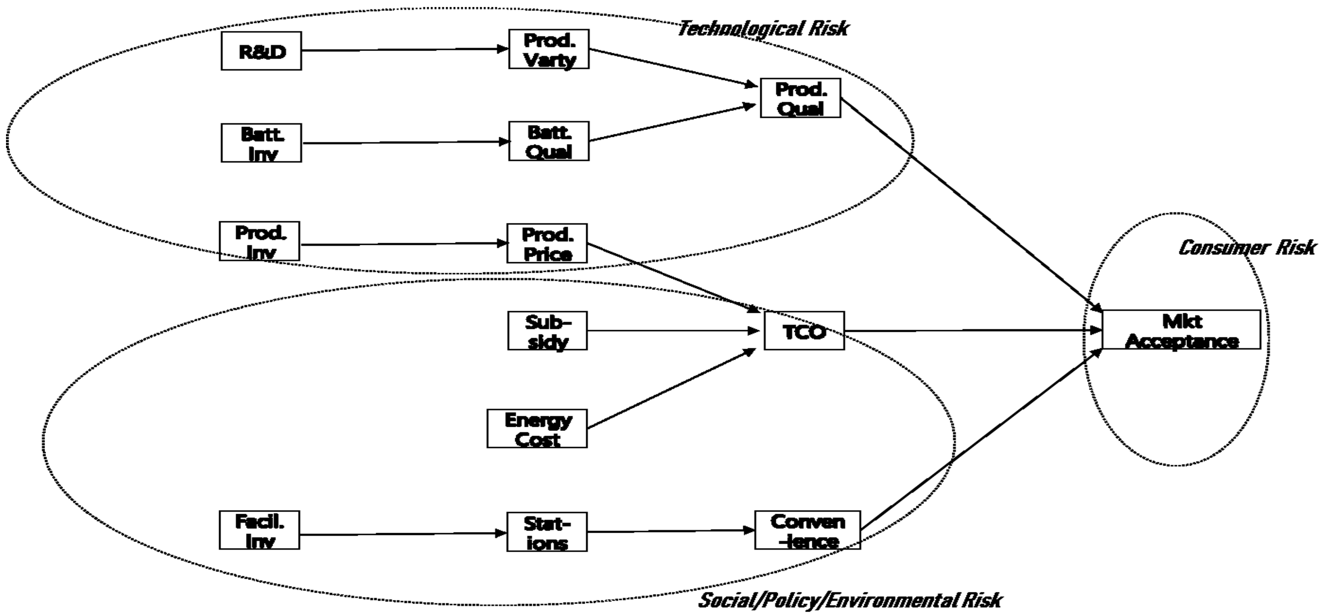

Figure 1: New Product Risk applied to EV Industry Ecology

3.1. Bayes Belief Network

A Bayes belief network is a graphical probabilistic model that represents a set of variables (nodes) and their conditional probabilities (Jensen 1996). Often there is more than one layer of cause and effect, so the relationship is modeled hierarchically. For example, in Figure 1, if we examine the bottom arrows, we have the case where "investment in charging facilities (Facil. Inv.)" leads to more "charging stations (Stations)," which then leads to greater "convenience," with the final result of greater "market acceptance." All such relations with nodes being connected by arrows will be modeled as a conditional probability in a Bayes belief network. Due to the advantage of estimating the whole structure, Bayes belief model has been applied widely in various fields of medicine, management and new product development (Landuyt et al., 2013; Chin et al., 2009).

3.2 Typography of Risk in the Electric Vehicle Industry

Technological risk is the uncertainty surrounding the successful development and production of EVs given a fixed level of investment. In particular, investment is broadly categorized into R&D, battery technology and production facilities. These investments will affect the next level of variables which are product variety (i.e., number of electric vehicle models offered), battery quality and product's price achieved through efficient manufacturing. In the model, we assume that R&D investment will increase product variety; that battery investment will increase battery quality; and that production facilities investment will decrease product price. It can be argued that R&D investment will also affect product price, but it is not clear in which direction, so we assume that R&D investment will not affect product price. Also, it can be argued that battery technology will decrease product price, as battery prices decrease. However, another way to look at this issue is to keep the battery price fixed, in which case developments in battery technology will increase battery capacity., thus increasing battery quality. Since battery technology is about how much it will cost to produce a Kwh of battery capacity (i.e., battery quality), technology improvements will either increase battery capacity or decrease price. One can fix one of the variables and measure improvements in the other variable. For this study, we assumed that investments in battery technology will increase battery quality while holding battery price fixed.

Finally, product quality is a composite measure comprising of both product variety and battery quality. For the consumer, one of the limitations of EVs today is the lack of models. Manufacturers have announced that they are planning to introduce many more models in the future, which requires greater investment in product R&D. Also, consumers still have *range anxiety*, the fear of being stranded without power. The increase in battery quality will substantially alleviate this worry and contribute to the overall product quality of EVs.

Another aspect of consumer acceptance of EVs is the total cost of ownership (TCO). The total cost of ownership is the average monthly cost of operating a vehicle. It is comprised of car depreciation, auto insurance cost, fuel cost, and repair & maintenance cost. TCO is often calculated for different car models and car types in order to make comparisons of economic advantages between different car options (e.g., model and car type). In particular, product price after government subsidies as well as the residual value of the EV after a certain period of use will determine the average rental/lease/payment per month for the consumer. Here it is important to note that subsidies can have a large impact on TCO. For example, a $10,000 subsidy on a $40,000 sub-compact EV will make the EV much more affordable to a buyer, making the EV price considerably closer to a comparable ICV. However, for many countries, the number of subsidies will be determined by how badly society wants EVs. One of the major factors that determine a society's need for EV is the acuteness of its air quality problem. For example, in China and Korea, the degradation of air quality in the metropolitan cities is an important impetus for the adoption of EVs. The pressing need for EVs has affected the level of subsidy that is being offered. Thus air quality is an environmental risk, but ironically, also an opportunity for the EV industry. Nevertheless, as the price of EVs decrease due to technological progress, there can be a commensurate decrease in the level of subsidies. Some governments are also exploring non-monetary incentives.

Electricity charging rates will also affect TCO. It is widely true that the cost of energy for an EV is much lower than that of an ICV. For example, in Korea, a survey of actual owners of a sub-compact EV answered that the cost of energy is only about $20 per month. This is about 1/10 of the cost of fueling a comparable ICV in Korea (Chu et. al 2019). So, the absolute energy cost, as well as, energy cost relative to an ICV will be an important consideration in consumer choice.

Another important factor is the presence of charging facilities and the speed of charging. For many cities, there are gasoline filling stations probably within 10 minutes driving distance from anywhere in the city. However, such may not be the case with EV charging stations. Also, fueling a gasoline tank will probably take a maximum of 5 minutes. However as yet, the fastest chargers take about 40 minutes for a complete charge. Nevertheless, there are chargers being developed that can partially charge in 10 minutes, and governments are determined to greatly increase the number of these fast chargers. These developments promise to increase the convenience of driving EVs.

Market acceptance of EVs will depend on product quality including variety, TCO and operating convenience. These three characteristics can be built into a consumer choice model using a logit model of vehicle choice. In the logit model, a consideration set can be determined and the relative merits of an EV will be contrasted with an ICV.

4. Bayes Belief Network of New Product Risk

Bayes belief network is a methodology for inference, structure discovery and simplification of joint probability distribution by using the specific structures in the data. Assume a probability distribution with n variables $x_1, x_2, \ldots, x_J$. The joint probability function P can be expressed as follows.

$$\begin{aligned} &P(x_1, x_2, \ldots, x_J) \\ &= P(x_J|x_{J-1}, \ldots, x_1)P(x_{J-1}|x_{J-2}, \ldots, x_1) \\ &\quad \ldots P(x_2|x_1)P(x_1) \\ &= \prod_{j=1}^{J} P(x_j|x_{j-1}, \ldots, x_1) \end{aligned} \tag{1}$$

In a Bayes belief network, there is a tree-like structure with a parent (X) affecting the descendent (Z), as in X→Z. The probability distribution of the descendent is only conditional upon the values of the immediate parent. Let $x, y,$ and z be the specific values of the variables X, Y, and Z, respectively. If Z only has $x \in X$ and $y \in Y$ as its immediate parents, then we have, $P(z|x, y, a, b, \ldots) = P(z|x, y)$. We use this structure of the network to simplify the From Figure 1, we may construct a Bayes belief network as follows, by working backwards. First, we define the variables as follows.

Table 1: Variables in the Model

Level 1	Level 2	Level 3	Level 4
R&D Investment (x_1)	Product Variety (y_1)	Product Quality (z_1)	Market acceptance of EVs (MA_{EV})
Battery Investment (x_2)	Battery Quality (y_2)		
Facilities Investment (x_3)	Stations (y_3)	Convenience (z_2)	
Production Investment (x_4)	Product Price (y_4)	TCO (z_3)	
	Subsidy (y_5)		
	Energy cost (y_6)		

Relationship between Level 4 and Level 3 variables are modeled as a logit model. The market acceptance variable MA takes values 0 or 1, where 0 implies the choice of an ICV and 1 implies the choice of an EV. Thus the market acceptance of EV, MA_{EV}, can be expressed as follows.

$$MA_{EV} = \frac{\exp(\alpha+\beta_1 z_1+\beta_2 z_2+\beta_3 z_3)}{\exp(\alpha+\beta_1 z_1+\beta_2 z_2+\beta_3 z_3) + 1}$$

Relationship between Level 3, Level 2 and Level 1 variables can be modeled as a simple Bayes belief network. The model of product quality, z_1, is modeled as follows.

$$\begin{aligned} &P(z_1, y_1, y_2, x_1, x_2) \\ &= P(z_1|y_1, y_2, x_1, x_2)P(y_1|y_2, x_1, x_2) \\ &P(y_2|x_1, x_2)P(x_1|x_2)P(x_2) \\ &= P(z_1|y_1, y_2)P(y_1|x_1)P(y_2|x_2)P(x_1)P(x_2) \\ &= P(y_1|x_1)P(y_2|x_2)P(x_1)P(x_2) \end{aligned}$$

Although most relationships are expressed as a conditional probability model, there are some deterministic relationships also. For example, we assume that $z_1 = f(y_1, y_2)$, so we have $P(z_1|y_1, y_2) = 1$. (i.e., z_1 is a deterministic function of y_1 and y_2).

Similarly, convenience, z_2, is modeled as follows by using the property of the Bayes network, and the assumption that $z_2 = g(y_3)$, so $P(z_2|y_3) = 1$. (i.e., z_2 is a deterministic function of y_3).

$$\begin{aligned} &P(z_2, y_3, x_3) \\ &= P(z_2|y_3, x_3)P(y_3|x_3)P(x_3) \\ &= P(z_2|y_3)P(y_3|x_3)P(x_3) \\ &= P(y_3|x_3)P(x_3) \end{aligned}$$

TCO, z_3, is modeled as follows by using the property of the Bayes network, and the assumption that $z_3 = h(y_4, y_5, y_6)$. So $P(z_3|y_4, y_5, y_6) = 1$. (i.e., z_3 is a deterministic function of y_4, y_5, y_6).

$$\begin{aligned} &P(z_3, y_4, y_5, y_6, x_4) \\ &= P(z_3|y_4, y_5, y_6, x_4)P(y_4|y_5, y_6, x_4) \\ &P(y_5|y_6, x_4)P(y_6|x_4)P(x_4) \\ &= P(z_3|y_4, y_5, y_6)P(y_4|x_4)P(y_5)P(y_6)P(x_4) \\ &= P(y_4|x_4)P(y_5)P(y_6)P(x_4) \end{aligned}$$

Finally, the conditional probability assessment given by our panel of 78 experts is denoted as $P_i(a|b)$. In our model the aggregate conditional probabilities are obtained by simple averaging.

$$P(a|b) = \frac{\sum_{i=1}^{N} P_i(a|b)}{N}$$

From this structure, we are able to estimate the market acceptance of the EV as a market share vis-à-vis the ICV, which is dependent on the initial investment (decision variable), state of the environment, and energy cost.

4.1. Values of Variables

The variables in the model were determined after interviews with a small group of industry analysts and from existing literature. The values were categorized as high, medium, low or just high and low, depending on the variable. A more granular categorization, while more exact, would have made the extraction of expert opinion too difficult in the subsequent data collection phase (i.e., opinion data from 78 experts). In this Bayes belief network, experts have to give a series of conditional probability distributions, regarding the relationship between the parent and descendent variables. Making the parent variable more granular increases the difficulty exponentially. Due to this practical limitation, the Bayes belief network was designed to be as simple as possible. We believe that this is an inherent limitation of applying Bayes belief network to expert data.

R&D Investment: This investment goes towards model development. It was assumed that a single model would cost about 300 billion won. The levels considered were 1 trillion won, 1.5 trillion won, and 2 trillion won.

Battery Investment: This investment goes towards increasing battery efficiency and cost. Investment in battery technology is usually made by battery manufacturers. Increasing investment can increase battery quality by generating more Kwh per unit cost. The levels of investment are assumed to be 500 billion won, 1 trillion won, and 1.5 trillion won

Production Investment: Although it is possible to assemble both ICVs and EVs in the same production line, mixing production is deemed inefficient for many reasons, one of them being the large differences in labor input between the two product types. This investment goes towards constructing a dedicated factory for EV assembly. The three levels of investment are 500 billion won, 1 trillion won, and 1.5 trillion won

Charging Facilities Investment: Many past studies of EV owners have cited the lack of charging facilities and long charging times as one of the most critical weaknesses of an EV. Due to this knowledge, governments are active in encouraging private businesses to invest in charging facilities. For Korea, the lack of real estate in the metropolitan areas and the fact that over 50% of the population live in apartment complexes have been identified as the bottlenecks in setting up charging facilities. Nevertheless, both the government and the industry realizes that continued investment is needed if EV is going to have meaningful sales in Korea. It was assumed that the average cost of installing a single high-speed charger is 20 million won. The two levels considered were 200 billion won and 400 billion won.

Product Variety: Product variety is also important for EV success. At the time of the survey, there were only 4 locally-produced EVs in Korea. By 2022, number product variety considered was 6 models and 12 models.

Battery Quality: Continuous progress in battery technology is assumed to take place. In the next three years, the per unit cost of battery output was assumed to decrease either 30%, 50% or 70%. This would translate into a quality (i.e., output in Kwh) increase of 40% , 100% and 330%, respectively, given the same cost.

Product Price: Price after subsidy is another important consideration for EV adoption. Currently, a compact EV (C segment) with 60Kwh battery output is around 35 million won after subsidy, while a comparable ICV is 16 million won. The current price ratio is 2.1 (=35/16). Therefore, assuming a continuous decrease in price, the three price ratio considered were 1.5, 1.3, and 1.0 (parity) after subsidy.

Subsidy: Subsidies are an important factor in EV adoption, as it increases the economic attractiveness of owning an EV. In Korea, consumer studies have shown the ceiling on EV adoption is the amount of budget available for subsidies. Even though the government has set a subsidy as high as 10 million won, this does not imply that everyone gets to benefit. The 10 million won is given out on a first-come-first-served basis until the budget runs out. Also, as battery prices continue to decrease, the cost offsetting role of subsidies becomes less necessary. Nevertheless, subsidies do play an important role in the proliferation of EVs. The three levels considered are (a) no subsidy, (b) 5 million won national subsidy plus 2 million won local government subsidy, and (c) 9 million won national plus 5 million local government subsidy.

Energy Cost: Energy cost for EVs is very low in Korea. One of the most often cited advantages of owning an EV in Korea was the low energy cost. In Korea, EV is charged a special discount price for as electricity, and there are numerous public charging stations that do not charge anything. The two levels considered was 30,000 won per month and 60,000 won per month for a mid-sized vehicle.

Number of Charging Stations: The two levels considered were 10,000 fast chargers and 20,000 fast chargers by 2022.

Product Quality: Product quality is a function of both product variety and battery quality. We assumed a deterministic function $z_1 = f(y_1, y_2)$. Since there are three values of y_1 and three values of y_2, there is a possible combination of 3x3 values.

Convenience: Convenience is given by the function $z_2 = g(y_3)$. Since there are three values of y_3, we will assume three values of z_2.

Total Cost of Ownership: The total cost of ownership is also obtained by a deterministic functional form, $z_3 = h(y_4, y_5, y_6)$. We will assume three values of z_3 as being higher than, equal to, and lower than that of an ICV.

Market Acceptance: Finally, market acceptance is modeled via a simulated choice experiment, estimated as a logit model. Given product variety, battery quality (range), convenience, and TCO, we may construct product profiles through the orthogonal design method. For the ICV, we will just have one benchmark case. The levels used in the choice experiment are shown in Table 2.

Table 2: Levels used in the Choice Experiment

EV	ICV
TCO = {550K, 600K, 700K} Convenience: - Easy to find charging stations, quick charge (20 mins) - Slightly inconvenient. Not enough charging stations. Charging time is 20 mins. - Inconvenient. Difficult to locate charging stations. Charging time is 40 mins. Driving range = {300km, 600km, 1000km} Car variety: - Can find the right car type and size - Can find the right car type, but choose a slightly different size (e.g., one size bigger or one size smaller) - Must compromise on the car type and size as there are not enough models	TCO = 600K Won Convenience: Easy to find and fill up gasoline Driving range = 800km Car variety: Can find the right car type and size

4.2. Estimation

Estimation of the NPRM model is shown in Table 3. From this table, we can assess the conditional probabilities of the benefit variables, z_i, by equations outlined above. The input to the Bayes belief network was from experts, described as professional working in automakers (R&D

sector), managers of EV parts manufacturers, and automobile industry watchers in government think tanks. A total of 78 experts gave their expert opinions on the risks associated with EV development, which became the input into the Bayes belief network model.

Table 3: NPRM Estimation

P(X)	P(Y|X)	P(Y)
Battery Investment (in trillion won) P(0.5)=1/3 P(1.0)=1/3 P(1.5)=1/3	Conditional Battery Quality (low, medium, high) P(L|0.5)=0.56, P(M|0.5)=0.26, P(H|0.5)=0.17 P(L|1.0)=0.48, P(M|1.0)=0.31, P(H|1.0)=0.20 P(L|1.5)=0.44, P(M|1.5)=0.30, P(H|1.5)=0.25	Battery Quality (low, medium, high) P(L)=0.50 P(M)=0.29 P(H)=0.21
R&D Investment (in trillion won) P(1.0)=1/3 P(2.0)=1/3 P(3.0)=1/3	Conditional Product Variety (low, medium, high) P(L|1.0)=0.58, P(M|1.0)=0.27, P(H|1.0)=0.15 P(L|2.0)=0.45, P(M|2.0)=0.33, P(H|2.0)=0.22 P(L|3.0)=0.35, P(M|3.0)=0.34, P(H|3.0)=0.30	Product Variety (low, medium, high) P(L)=0.46 P(M)=0.31 P(H)=0.23
Production Invest. (in trillion won) P(0.5)=1/3 P(1.0)=1/3 P(1.5)=1/3	Conditional Product Price (low, medium, high) P(L|0.5)=0.55, P(M|0.5)=0.28, P(H|0.5)=0.17 P(L|1.0)=0.48, P(M|1.0)=0.33, P(H|1.0)=0.19 P(L|1.5)=0.39, P(M|1.5)=0.33, P(H|1.5)=0.28	Product Price (low, medium, high) P(L)=0.47 P(M)=0.31 P(H)=0.22
Charging Facility Invest. (in trillion won) P(0.2)=1/2 P(0.4)=1/2	Conditional Charging Stations (low, medium, high) P(L|0.2)=0.55, P(M|0.2)=0.28, P(H|0.2)=0.17 P(L|0.4)=0.38, P(M|0.4)=0.34, P(H|0.4)=0.28	Charging Stations (low, medium, high) P(L)=0.46 P(M)=0.31 P(H)=0.23

4.3. Choice Experiment and Logit Model

In order to conduct the experiment, a total of 4 factors and $3^4 = 81$ profiles were reduced to 9 orthogonal profiles by the orthogonal design procedure, as in Table 4.

Table 4: Orthogonal Design

Product Variety (z_{11}) (Model availability)	Battery Range (z_{12})	TCO (z_3) Per month	Charging Convenience (z_4)
Right Car Type & Size	600 km	600,000 won	Inconvenient
Right Car Type & Size	1000 km	450,000 won	Slightly Inconvenient
Find Car Type at Next Level	300 km	600,000 won	Slightly Inconvenient
Find Car Type at Next Level	1000 km	500,000 won	Inconvenient
Find Car Type at Next Level	600 km	450,000 won	Many stations, Quick Charge
Must compromise type & size	1000 km	600,000 won	Many stations, Quick Charge
Must compromise type & size	300 km	450,000 won	Inconvenient
Right Car Type & Size	300 km	500,000 won	Many stations, Quick Charge
Must compromise type & size	600 km	500,000 won	Slightly Inconvenient

In the experiment, the subject is given a choice of an EV profile and an ICV profile. A subject was shown one EV profile against the ICV profile.

EV Profile: (z_{11}, z_{12}, z_3, z_4)

ICV Profile: right car type and size, range of 800Km, TCO of 50,000 won per month.

After the EV profile is provided, the respondent is asked the following two questions.

Please rate the EV. How attractive is it to purchase?

(1)Very unattractive (2) Slightly unattractive (3) Acceptable (4) Attractive (5) Very attractive

If you had the choice between the EV and the Gasoline car, which would you choose?

EV_____
ICV ______

The experiment was administered to 55 respondents, who were students and Korean executives taking management courses at a major Korean university. Since each respondent answered 9 simulated choice questions, we obtained a total of 495 (=55 x 9) choice samples. From a choice experiment, the following results were obtained by the logit model (Table 4). The first question on preference can be used to conduct conjoint analysis, and the second question can be used to estimate a logit model. All the analyses were carried out at the group level. The part-worth utility from the conjoint analysis is shown in Table 5. The conjoint model was estimated by dummy-variable regression. The parameters of the dummy variables represent the part worth of the levels of each attribute.

Table 5: Part-Worth Utility from Dummy-variable Regression

	Coefficients B	Std.Error	Standardized CoefficientsBeta	t	sig
(Constant)	1.339	.171		7.838	.000
Variety2 (M)	.582	.140	.168	4.170	.000
Variety3 (H)	.988	.140	.286	7.081	.000
Battery2 (M)	1.073	.140	.310	7.689	.000
Battery3 (H)	1.588	.140	.459	11.381	.000
TCO2 (M)	.782	.140	.226	5.604	.000
TCO3 (L)	1.570	.140	.454	11.251	.000
Convene2(M)	.406	.140	.117	2.910	.004
Convene3 (H)	.618	. 140	.179	4.431	.000
Dependent Var. Preference; Default cases are Variety1(L), Battery1(L), TCO1(H), Convene1(L)					

From Table 5, the importance weights of each variable at the levels tested can be deduced, as follows. Since the default case is set to zero, the importance of each variable is the difference between zero and the level that gives the highest part worth. From the conjoint study, it can be concluded that battery performance and TCO are the most important factors, followed by model variety.

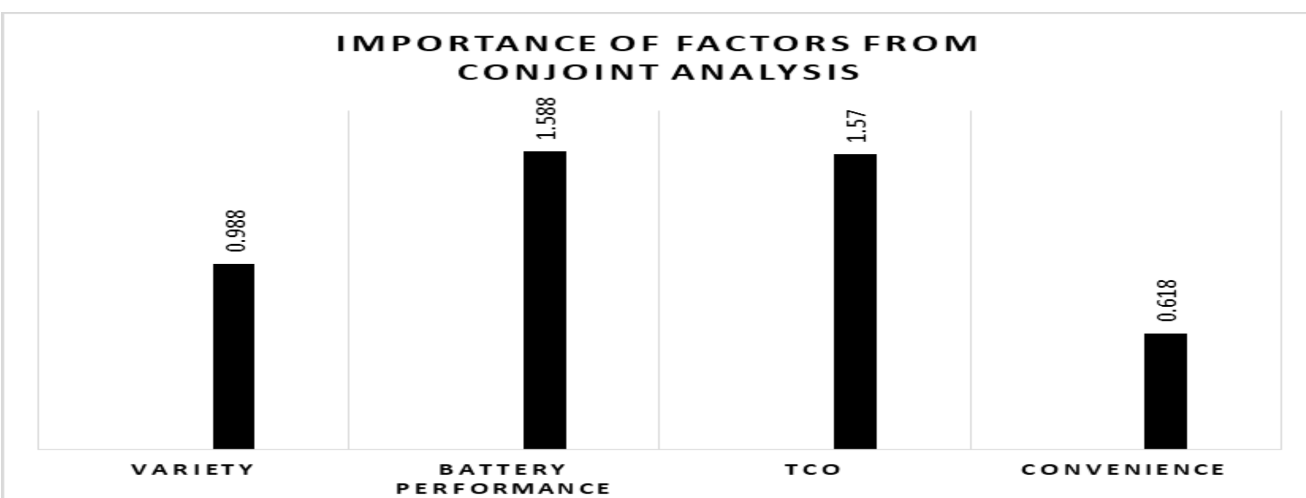

Figure 2: Importance of Factors

Table 6: Estimates of the Logit Model

	Coefficients B Std.Error	t	sig
(Constant)	- .327 .053	-6.215	.000
Variety2 (M)	.164 .043	3.806	.000
Variety3 (H)	.242 .043	5.639	.000
Battery2 (M)	.212 .043	4.934	.000
Battery3 (H)	.339 .043	7.894	.000
TCO2 (M)	.188 .043	4.370	.000
TCO3 (L)	.473 .043	10.996	.000
Convene2(M)	.182 .043	4.229	.000
Convene3 (H)	.224 .043	5.216	.000
Dependent Var. Choice (0:ICV, 1:EV); Default cases are Variety1(L), Battery1(L), TCO1(H), Convene1(L)			

To estimate market acceptance, we use the conditional logit choice model. The estimation of the conditional logit model is shown in Table 6.

$$MS_{ijkl} = \frac{e^{\alpha+\beta_1 z_{11}(i)+\beta_2 z_{12}(j)+\beta_3 z_3(k)+\beta_4 z_4(l)}}{e^{\alpha+\beta_1 z_{11}(i)+\beta_2 z_{12}(j)+\beta_3 z_3(k)+\beta_4 z_4(l)}+1}$$

The estimated utility is presented as

$$U = .327 + .164\,Variety(M) + .242\,Variety(H)$$
$$+ .212\,Battery(M) + .339\,Battery\,(H)$$
$$+ .188\,TCO(M) + .473\,TCO(L)$$
$$+ .182\,Convene(M) + .224\,Convene(H)$$

It is noted that the TCO variable is such that TCO(H) is given a default estimate of zero. Therefore, it is consistent with our assumption that TCO(L) gives the highest utility, with TCO(M) in between.

The final forecasting model is derived by combining Table 2 and Table 4 as follows, where *i, j, k, l* represents the subscripts for variety, battery, TCO and convenience, respectively.

$$MS = \sum_{i=1,2,3}\sum_{j=1,2,3}\sum_{k=1,2,3}\sum_{l=1,2,3} P_i P_j P_k P_l\, MS_{ijkl}$$

The final market share estimate, assuming that each level of investment is equally likely is given as,

$$MS = .555$$

This estimate is rather high, but it is the estimated market share assuming continued investment by companies and governments. As such, the figure represents the potential market share that is possible in the next three years.

5. Conclusion and Discussion

NPRM (New Product Risk Model) is an integrative model that is able to estimate the total ecology of the EV industry. Previous literature on EVs has only examined one component, rather than the complex inter-relationships of the total ecology. Some papers have examined the total cost of ownership (Breetza and Salon 2018), some have focused on consumer choice (Chu et al., 2019), some have focused on technology (Feng et al., 2020), while some have focused on government incentives (Jenna et al. 2018). The benefit of using Bayes belief network is the ability to integrate the sub-systems under a common denominator of probability. This is the major theoretical contribution of this study.

As environmental concerns continue to be on the minds of the public, EVs will be viewed as an important alternative to ICVs. Even though EVs have to ultimately rely on some form of fuel to generate electricity, the benefits of EVs is in decoupling the place of energy use with energy generation. Therefore, EVs are usually welcomed by municipal governments of metropolitan cities, since the place of use does not have to suffer the pollution of car emissions. However, since electricity has to be generated, the assumption is that generating electricity on a large scale and transmitting them through cable must be more fuel-efficient than burning gasoline or diesel in a combustion engine.

The auto industry and governments have already shifted its focus from EVs to ICVs. However, EVs are not selling at a rate that would make it profitable for automakers. Also, governments are experimenting with different incentives to make EVs diffuse faster in their respective countries. This is why more understanding of the industry is required. The success of EVs cannot be viewed solely as a management challenge. Many factors that are beyond the control of automakers could have an effect on EV sales. As such, the EV industry and market need to be examined from a macro-perspective.

This research presented an integrative model of EV success in the market and the risks that are involved. The risk was categorized into technological, social/policy, environmental, and consumer risk. Technological progress is primarily affected by company investment levels. More investment can increase the chances of producing a higher quality EV, but the investment-quality relationship is not deterministic. It is more accurate to say that more investment will shift the probability distribution of the quality variable to the right. Another risk is policy risk. Sudden shifts by governments on monetary incentives for EVs will produce shocks in the market that automakers will have to bear. Also, to date, monetary incentives seem to be the most important variable, together with battery quality, in determining consumer adoption of EVs. Government policy in turn is motivated by public demand for more EVs. To finish the cycle, public demand for EVs is determined by the degree of environmental deterioration, which is the environmental risk, or opportunity for the EV industry. Finally, consumer risk is the consumer acceptance of EVs, which will be determined by the relative advantage of owning an EV compared to an ICV.

NPRM (New Product Risk Model) is an integrative model that encompasses all four risk categories (technological, social-policy, environmental, consumer). The model is a system of conditional probability distributions employed in a simple Bayes network. Each of the variables mentioned is linked to the other variables through a conditional probability distribution. The final outcomes are then used to form an orthogonal design, which is then presented to consumers in a simulated choice experiment (i.e., conditional logit). The conditional logit model is used to estimate the market share of EVs for a single outcome configuration. Each outcome configuration is assigned a probability from the NPRM. The final market share estimate is obtained by a weighted average of each market share estimate multiplied by the probability of that outcome.

NPRM is a useful simulation tool. It can provide answers to the following management or policy questions.

- The relationship between the level of each investment (battery, production, product R&D) and EV market success.
- The relationship between each level of government subsidy and EV market success
- The relative importance of various factors (i.e., product variety, battery range, total cost of operation, charging convenience)
- Probability of each scenario as a function of industry investment and government incentives
- Market share simulation

NPRM is qualitatively superior to previous models of risk for the following reasons.

- Industry, government and consumer actions are integrated into a single EV market success outcome
- Diverse dimensions are integrated via a common denominator of conditional probability
- The data input is from a panel of experts who are stakeholders in the EV environment. The number of experts (N=78) and the breadth of panel representation (automaker, EV parts supplier, government think tank) is unique in new product risk research.
- The model is amenable to extensions to more factors

The substantive outcome of the NPRM is the stipulation of diverse levels of investment and outcomes. Expert opinion as to what amount constituted high, medium or low levels for each variable is also a valuable benchmark for future stakeholders to consider.

NPRM also has limitations. The expert opinion approach used here severely limits the complexity of the model as respondents have a hard time giving probability distributions for a variable with more than three levels. Some respondents have felt that the questions were rather time-consuming and difficult to answer. Bayes belief networks are best used with large data sets, where data is collected in large amounts automatically. In such instance, data input is automatic and the researcher just needs to assign relationship and let the model provide the conditional probability distributions. However, development in data query methods using Bayes belief networks promises the possibility of using the methodology with experts.

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