Effects of User Experience on User Resistance to Change to the Voice User Interface of an In-vehicle Infotainment System: Implications for Platform and Standards Competition

Dong-hyu Kim, Heejin Lee

Abstract

This study examines the effects of user experience on user resistance to change—particularly, on the relationship between user resistance to change and its antecedents (i.e. switching costs and perceived value) in the context of the voice user interface of an in-vehicle infotainment (IVI) system. This research offers several salient findings. First, it shows that user experience positively moderates the relationship between uncertainty costs (one type of switching cost) and user resistance. It also negatively moderates the association between perceived value and user resistance. Second, the research test results demonstrate that users with a high degree of prior experience with the voice user interface of other smart devices exhibit low user resistance to change to the voice user interface in an IVI system. Third, we show that three types of switching costs (transition costs, in particular) may directly influence users to resist a change to the voice user interface. Fourth, our test results empirically demonstrate that both switching costs and perceived value affect user resistance to change in the context of an IVI system, which differs from the traditional IS research setting (i.e. enterprise systems). These findings may guide not only platform leaders in designing user interfaces, user experiences, and marketing strategies, but also firms that want to defend themselves from platform envelopment while devising defensive strategies in platform and standards competition.

Key words: user resistance, user experience, user interface, infotainment system, platform, standard

I. Introduction

Omnipresent mobile connectivity has increasingly become a part of the fabric of everyday life, and it is seamlessly integrated into the in-vehicle environment in the form of infotainment systems. The concept of "infotainment" represents a marriage of information and entertainment; an in-vehicle infotainment (IVI) system not only provides users with navigation and traffic information, but also amuses them with music and videos. As a result, people have now started to see their car not merely as a means of mobility, but also as a versatile means of satisfying a variety of needs.

Recognizing burgeoning consumer demand, Apple, one of the world's leading information technology (IT) firms, introduced CarPlay to the IVI system market, in March 2014. CarPlay allows access to Apple devices based on its operating system (iOS), via display units on automobile dashboards.

Formatted: Font: Times New Roman, Check spelling and grammar

Its user interface is consistent with that seen on other Apple iOS devices and, as a result, users may face little difficulty in controlling new infotainment systems. Competing with Apple's CarPlay, Google unveiled in June 2014 its IVI system Android Auto, which extends the functionality of an Android device to the automobile environment. Many car manufacturers—including Audi, BMW, Chrysler, Ferrari, Fiat, Ford, Honda, Hyundai, Mercedes-Benz, Nissan, Toyota, and Volvo—have already exhibited an interest in implementing CarPlay and/or Android Auto in their automobiles.

The Apple and Google platforms have dominated in the global smartphone industry, establishing a *de facto* duopoly that accounted in 2014 for over 90% of smartphone sales worldwide (GSMA Intelligence, 2014). Now, with the aid of technological advances, the dynamics of mobile platforms competition have cascaded into other industries, including connected cars, and blurred traditional industry boundaries. This mobile platform-driven large-scale industry convergence has been pressing other industry players to position themselves in a complex, multi-layered technological space that features a variety of core competencies and platform strategies (Kenney & Pon, 2011).

Platforms, in general, comprise three constitutive elements—namely, a core technology, modular technologies that connect with the core, and the interfaces in-between (Baldwin & Woodard, 2009). Some platforms serve as multi-sided markets, where bringing multiple sides of the market on board (i.e. a large installed user base and a great number of complementary goods for network effects (Katz & Shapiro, 1985)) assumes crucial roles in platform competition (Eisenmann, Parker, & Alstyne, 2006; Evans, 2003; Rochet & Tirole, 2003). In this context, user interfaces and user experience have become of particular importance in attracting users and, in turn, increasing the value of platform networks. For instance, Apple's success with its iPhone can in part be attributed to its user interface—which features intuitive panning and zooming designed for a touchscreen—and to its tight control over an ecosystem of complementary firms (called a "walled garden" strategy); doing so created an effective and cohesive user experience, and "locked" users into Apple's iOS platform (Kenney & Pon, 2011; West & Mace, 2010). In 2011, when Apple integrated into its iOS "Siri" (the voice user interface-based app by which to improve information searches and the user experience while using Apple devices), Google considered this a competitive threat to its core search business[1] (Schmidt, 2011); it responded by rolling out Google Now, its enhanced voice search engine, in 2012.

Enhanced voice control in the user interface is one of the main differentiators between existing systems and Apple and Google's IVI systems. The installation of the voice recognition programs Apple Siri and Google Now into IVI systems enables the use of voice user interface-based applications, through which users can carry out eyes and hand-free operations in a manner similar to that seen with

[1] In 2012, 95% of Google's revenue was generated from advertising via its search engine (Pon, Seppälä, & Kenney, 2014).

Formatted: Font: Times New Roman, Check spelling and grammar

other iOS and Android devices. Switching to a voice user interface from a touch-based interface in an IVI system can offer users a number of potential benefits, such as quick access to services and less distraction from driving. It has been shown that auditory feedback may offload information from the visual modality and thereby reduce the user's cognitive workload (Burke et al., 2006). Despite the benefits stemming from the use of a voice interface, a majority of users mainly rely on a touch-based interface in an IVI system, given their dissatisfactory prior experiences with ill-functioning voice recognition programs (Kessler & Chen, 2015). This kind of user experience is likely to catalyze user resistance against the new voice-activated applications that Apple's CarPlay and Google's Android Auto will offer.

User resistance to change has been one of the important research topics in information systems (IS) studies. Kim and Kankanhalli (2009) and Kim (2011), for instance, each developed a research model while drawing on status quo bias theory (Samuelson & Zeckhauser, 1988); they each demonstrate that switching costs constitute the main determinant of user resistance to change. Nonetheless, these studies did not examine the effect of users' prior experience on user resistance to change—particularly, on the relationship between user resistance to change and its antecedents. Prior experience influences later behaviors, as it shapes realistic expectations. Some studies show that user experience moderates the impact of attitudinal beliefs (e.g. perceived ease of use and perceived usefulness) on behavioral intention (Castañeda, Muñoz-Leiva, & Luque, 2007; Gefen, Karahanna, & Straub, 2003). This also affects all the factors that determine the behavior in question, in an overall manner (Ajzen, 1991). From these prior studies, it is presumed that user resistance to change and its relationship with its antecedents (i.e. switching costs and perceived value) vary with user experience. Nonetheless, few researchers have paid attention to the effect of user experience on user resistance. To fill this research lacuna, we address a research question: how does user resistance to change vary with degree of user experience with the voice user interface?

In addition to addressing said research question, this study also attempts to apply the findings of previous research studies on user resistance to change (Kim & Kankanhalli, 2009; Kim, 2011)—most of which were derived primarily by examining the implementation of enterprise systems—to a different IS context (i.e. user interfaces of IVI systems). Such an attempt not only advances research on user resistance to change, but also sheds light on the ongoing phenomenon of platform and standards competition that revolves around a user interface. The growing importance of user interfaces in platform and standards competition gives this study a practical *raison d'être*.

In the subsequent section, we explain three main concepts (i.e. user resistance to change, switching costs, and user experience) and the conceptual framework used in this study. Section three describes our research model and hypotheses. We then present the research methodology in section four and report the results of hypotheses testing in section five. Thereafter, we discuss our results and their

Formatted: Font: Times New Roman, Check spelling and grammar

theoretical/practical implications, and reflect on those implications with respect to contemporary platform and standards competition.

II. User Resistance to Change, Switching Costs, and User Experience

A. User resistance to change

Resistance to change has been extensively studied in a variety of academic fields—in IS, in particular. Many IS researchers who have delved into the failure of new IS implementation in an organization identify user resistance to change as a fundamental factor (Hirschheim & Newman, 1988; Lucas, 1975; Lyytinen & Hirschheim, 1987). In general, "resistance to change" refers to any conduct in line with attempting to maintain the status quo, and as persistence in avoiding change (Pardo del Val & Martínez Fuentes, 2003; Rumelt, 1995). Similarly, user resistance to change in IS research is conceptualized as user opposition (Markus, 1983) or adverse reaction (Hirschheim & Newman, 1988) to proposed changes in IS implementation. In this study, "user resistance to change" refers to the *opposition of a user to change associated with a new way of working with a user interface*.

As Lapointe and Rivard (2005) point out, while plenty of studies expressly address the concept of user resistance, only a few provide theoretical explanations of the mechanisms therein (Joshi, 1991; Marakas & Hornik, 1996; Markus, 1983; Martinko, Zmud, & Henry, 1996). Joshi (1991) relies on equity theory to elucidate user resistance: in essence, users resist if they perceive negative inequity (i.e. greater changes in input vis-à-vis output). Marakas and Hornik (1996) adopt the notion of passive aggressive (P–A) behavior to explicate user resistance as P–A responses to real or perceived threats or to stress associated with a new IS. They argue that the uncertainty that accompanies a new IS implementation may engender conditions under which resistance behavior can manifest among users. Markus (1983) categorizes three causes of user resistance—namely, 1) internal factors that mediate interactions among people and groups, such as cognitive orientations, 2) system factors, such as poor technical design and lack of user-friendliness, and 3) interaction between system and context of use. Resting on a political variant of interaction theory, she explains user resistance in the perspective of the distribution of intra-organizational power, and predicts that potential loss of power will beget resistance by a group of users to IS implementation. Martinko et al. (1996) propose an attribution model that posits that users' perceived causal attributions for success/failure (i.e. ability, effort, task difficulty, luck/chance) influence their expectations about outcomes and efficacy, and thereby drive behavioral reactions with regard to IS implementation. Particularly, users' prior experience with similar technology is a critical factor that evokes causal attributions.

Building upon four earlier models that conceptualize user resistance, Lapointe and Rivard (2005) put forth a multilevel model based on five components: behaviors, object, subject, threats, and initial conditions. The interaction between a given set of initial conditions at the individual or organization level and an object (e.g. system features) results in perceived threats (e.g. distress of inequity), and thereby resistance behavior. Following IS implementation, actual experiences and other triggers recursively affect the conditions of interaction. From all the aforementioned models, we identified net equity (i.e. difference between changes in input and output), perceived threats associated with situational conditions (e.g. uncertainty), users' prior experience, and the interaction of antecedents as important determinants of user resistance. Net equity can be estimated on the basis of a cost–benefit analysis of an expected change. Perceived costs or threats associated with the change which substantially affect user resistance are considered switching costs.

B. *Switching costs*

The literature discusses switching costs in a wide variety of ways. The concept, in turn, is defined in various ways—for instance, the disutility related to change (Chen & Hitt, 2002; Weiss & Anderson, 1992), relationship-specific investments between buyers and suppliers (Farrell & Shapiro, 1988; Jackson, 1985) and the costs of dissolving a contractual relationship (Porter, 1980), and the combination of psychological and economic costs associated with changing from one alternative to another (Jones, Mothersbaugh, & Beatty, 2002; Klemperer, 1987). Kim and Kankanhalli (2009) define switching costs as constituting the *perceived disutility a user would incur by switching from the status quo to a new situation* (e.g. working with new systems that use a new user interface). Switching costs in this study are understood in line with the definition of Kim and Kankanhalli.

The economics literature places emphasis on the effect of switching costs on competition in the market. After identifying three types of switching costs (i.e. transaction costs, learning costs, and artificial/contractual costs), Klemperer (1987) makes two points. First, switching costs divide the market into submarkets, and thereby reduce competition; second, before undertaking market segmentation on the basis of switching costs, firms engage in fierce competition to gain monopolistic gains over their respective market segments. Contrary to the widely accepted belief that switching costs serve as an entry barrier (Porter, 1980), Farrell and Shapiro (1988) suggest that switching costs may actually trigger excessive entry. This, they argue, is because when switching costs exceed economies of scale or network externalities, incumbents tend to exploit existing locked-in customers and allow new entrants to serve other groups of customers who are unattached to the incumbents.

Marketing research highlights the relationship between switching costs and customer retention. Jones et al. (2002) developed multidimensional scale items for six types of switching costs: 1) lost-

Formatted: Font: Times New Roman, Check spelling and grammar

performance costs, 2) uncertainty costs, 3) pre-switching search and evaluation costs, 4) post-switching behavioral and cognitive costs, 5) set-up costs, and 6) sunk costs. They also identify industry-unique differences in the effect of switching on repurchase intentions—for instance, both set-up costs and pre-switching search and evaluations costs more strongly correlate with repurchase intentions for hairstylists than for banks. Lai, Liu, and Lin (2011) found that switching costs enhance the moderating effect of inertia-produced locked-in behaviors on the relationship between satisfaction and customer retention, driving even dissatisfied customers to stay with their existing suppliers.

The moderating effects of switching costs on the relationship between satisfaction and customer retention have evidenced variability in previous literature. Jones, Mothersbaugh, and Beatty (2000) showed that switching barriers—including perceived switching costs—negatively moderate the relationship between core-service satisfaction and repurchase intentions. Their explanation was that consumers consider switching costs in the process of retention only when the level of satisfaction is low. By contrast, Yang and Peterson (2004) found a positive moderating effect of switching costs on the association of customer loyalty with satisfaction only when the level of satisfaction was higher than the average, while there was the overall lack of a significant moderating effect for switching costs. These conflicting evidence reveal the complex processes of the interaction between switching costs and satisfaction. Considering that satisfaction is heavily affected by expectations based on prior experience (Oliver, 2010), it is likely that prior experience contributes to the various moderating roles of switching costs. This underpins the objective of the current study, i.e. an investigation on the interaction between switching costs and prior experience.

With respect to empirical tests on the effect of switching costs on user resistance to change, Kim and Kankanhalli (2009) and Kim (2011) each developed a research model grounded on status quo bias theory (Samuelson & Zeckhauser, 1988) and the equity-implementation model (EIM) (Joshi, 1991). While Kim and Kankanhalli (2009) conceptualize switching costs as unidimensional, Kim (2011) pays heed to the literature that proposes multiple types of switching costs (e.g. Burnham, Frels, & Mahajan, 2003; Jones et al., 2002; Klemperer, 1987; Whitten & Wakefield, 2006), and operationalizes the multidimensional nature of switching costs. In the context of this body of research, we modify and use the types of switching costs classified by Kim (2011) on the basis of status quo bias theory.

C. *User experience*

The influence of prior experience on users' choices has been an intriguing topic in the field of consumer research. This stream of literature relies on information processing theory to expound the effect of user experience. Hayes-Roth (1977) and Marks and Olson (1981) each contends that users' prior experience in the form of product familiarity assists them in establishing knowledge structures or "schemata,"

Formatted: Font: Times New Roman, Check spelling and grammar

which contain evaluative standards and rules (Rao & Monroe, 1988). Schemata developed through past experiences enable heuristic information-processing (i.e. the use of “rules of thumb”) (Abelson, 1976; Stotland & Canon, 1972). Unlike a systematic view that stresses the detailed and organized processing of information, heuristic information-processing leads users to rely on simple cues during decision-making (Chaiken, 1980).

Users’ experiences influence the availability and accessibility of heuristics (Chen & Chaiken, 1999). This means that different degrees of prior experience in the form of product familiarity give rise to differentially developed schemas, which in turn affect heuristic cues (Park & Lessig, 1981). Less-experienced users need more time to develop evaluative standards for choice comparisons (Bettman & Park, 1980) and, therefore, they tend to engage in extensive problem-solving (Howard, 1977). More-experienced users are likely to capitalize on intrinsic cues derived from a product itself (e.g. product attributes) during product assessments, whereas less-experienced users are inclined to draw on extrinsic cues (e.g. prices) (Olson, 1977; Rao & Monroe, 1988). Similarly, in the evaluation of a certain brand, users with relatively high degrees of prior experience tend to focus on utilitarian (or intrinsic) cues, while those with less experience are expected to rely on user-image (or extrinsic) cues (Mangleburg et al., 1998). It is because that, as Wood and Kallgren (1988) reasoned, those who have a dearth of attitude-relevant information accessible in memory, partly due to little prior experience, are less likely to process message contents (intrinsic cues) and, accordingly, more likely to be influenced by non-message cues (extrinsic cues).

Heuristic effects based on prior experience should be carefully addressed as early studies often refer to extrinsic cues-based cognition (e.g. relying on source credibility) as heuristic or peripheral processing (Chaiken, 1980; Petty & Cacioppo, 1986; Wegener, Petty, Blankenship, & Detweiler-Bedell, 2010). In fact, previous literature (e.g. Bettman & Park, 1980) has found that highly experienced and inexperienced users process information in a heuristic way, whereas moderately experienced users take a more systematic approach. Despite using the same terminology, the heuristic processes between highly experienced users and inexperienced users differ. Highly experienced users have accumulated experience around the most relevant and important cues and, in turn, swiftly and extensively utilize such information as a decision-making criterion (Gupta & Kim, 2007). In contrast, inexperienced users who lack relevant information accessible in memory, particularly with a low level of issue involvement, tend to rely on extrinsic cues.

Planned behavior theory (Ajzen, 1991) can also be used to explain the role of user experience in IS usage behavior. The theory incorporates perceived behavioral control (i.e. people’s perceptions of the ease or difficulty of performing the behavior of interest) as a predictor of intention and behavior. People perceive themselves as having greater control over their behavior when they expect fewer obstacles or impediments, and when they possess more resources and opportunities. Prior experience is

Formatted: Font: Times New Roman, Check spelling and grammar

the most important information source to influence those control beliefs (Bandura, 1986). The acquisition of knowledge from prior experience makes control factors more accessible. Considerations of control factors shape the formation of realistic expectations (Sheppard, Hartwick, & Warshaw, 1988), thus constructing a stronger link between intention and behavior. Taylor and Todd (1995) found that users with a lower degree of past experience may place greater emphasis on the potential benefits of IS usage and underrate the costs incurred, while more-experienced users tend to take into account control information in the formation of expectations.

The literature on lock-in also stresses the influence of past behavior on future events, in what is known as path dependency. User expectations constitute a main source of self-reinforcing mechanisms that result in path dependency (Arthur, 1994). As stated, prior experience can substantially influence these self-fulfilling expectations. The lock-in effect is discussed in detail in David's (1985) well-recognized example of the QWERTY text-entry interface. Despite its inherent inefficiency, the QWERTY-based touch interface locked users in, and was established as the *de facto* industry standard. He emphasizes that path dependency, as a main factor, contributes to the lock-in effect. David argues that the lock-in effect may occur when there are strong technical interrelatedness, economies of scale, and irreversibility due to learning and habituation.

With a focus on the notion of behavioral lock-in (i.e. habit-driven irreversibility), Barnes, Gartland, and Stack (2004) point out that habituation is highly associated with status quo inertia. Polites and Karahanna (2012) demonstrate that habitual use and switching costs both influence inertia, considering inertia a form of user resistance to change that reflects status quo bias. The constraint factors of inertia and switching costs substantially affect the behavior of users who continue to use IT products (Lin, Huang, & Hsu, 2015). The relationship between switching costs and the behavior of users who stay with current products and services tends to be stronger when users have had a longer period of usage (Deng, Lu, Wei, & Zhang, 2010).

The accumulation of prior experience also lays the foundation for the formation of a habit. Although the frequency of past behavior highly correlates with habit, prior experience and habitual use can be conceptualized and operationalized in different ways (Polites & Karahanna, 2012). As Ajzen (1991) points out, the effect of user experience can be reflected in all factors that determine the behavior of interest (i.e. user resistance to change, in this case). Some researchers (e.g. Bentler & Speckart, 1979) have suggested that past experience may have substantial residual effects beyond the antecedents contained in the model; if this be so, such residual effects would presumably be reflected in the influence of habit and, in turn, contribute to the lock-in effect.

III. Research Model and Hypotheses

Formatted: Font: Times New Roman, Check spelling and grammar

Our research model is a modification of the model of Kim (2011), in the context of the user interface of an IVI system; we use this model to test the main effect of switching costs on user resistance to change and the moderating effect of user experience. Kim's model is conceptually predicated on the EIM (Joshi, 1991) and status quo bias research (Samuelson & Zeckhauser, 1988). The EIM finds net equity, assessed by comparing changes in input in terms of output, to be the primary factor behind user resistance. Increases in input and decreases in output may constitute switching costs (i.e. disutility), whereas decreases in input and increases in output constitute switching benefits. Net equity corresponds to perceived value, formed via an overall cost–benefit assessment of change.

As with the work of Kim (2011), status quo bias research provides us with the theoretical foundations for the components of switching costs with respect to user resistance to change, as found in our conceptual framework. Under status quo framing, one (default) choice is about maintaining the status quo or current position, while the other is about switching to an alternative. Samuelson and Zeckhauser (1988) classified the causes of status quo bias into three categories: 1) rational decision-making in the presence of uncertainty and/or transition costs, 2) psychological commitment (e.g. sunk costs), and 3) cognitive misperceptions. Three types of switching costs (two influencing a rational cost–benefit analysis and one affecting psychological reaction) can be highlighted in particular—namely, uncertainty, transition, and sunk costs. These are also mentioned in the literature as the components of switching costs (Jones et al., 2002; Klemperer, 1987; Whitten & Wakefield, 2006).

The term "uncertainty costs" refers to negative psychological reactions to uncertainty that are associated with new situations and which bias subjects towards maintaining the status quo (Inder & O'Brien, 2003). While some studies differentiate uncertainty from risk (e.g. Knight, 1921), we follow Einhorn and Hogarth's (1986) and Inder and O'Brien (2003) definition of uncertainty, and understand uncertainty as a concept that encompasses both risk and ambiguity (i.e. known and unknown probabilities of possible outcomes). Under conditions of uncertainty, the value of an alternative is built on expectations in lieu of knowledge, and a gap between expectations and knowledge represents risks or switching costs (Whitten & Wakefield, 2006). Uncertainty costs tend to be high if a service is intangible and its outcomes are heterogeneous (Zeithaml, Parasuraman, & Berry, 1985).

The term "transition costs" refers to irreversible investments of time and effort in adapting to new situations (David, 1985; Samuelson & Zeckhauser, 1988). These costs relate to learning about new procedures and routines (Jones et al., 2002). "Sunk costs" refer to previous commitments that stimulate a reluctance to switch to a new alternative (Brockner et al., 1982). In this study, sunk costs are considered irrecoverable investments of time and effort spent in learning how to use a previous or current user interface. Although economic theory considers assessments of sunk costs irrational, it is often found that sunk costs serve as a psychological factor that affects the decision-making process (Keil, Mann, & Rai, 2000; Whitten & Wakefield, 2006).

Formatted: Font: Times New Roman, Check spelling and grammar

Loss aversion (i.e. when losses loom larger than gains (Kahneman & Tversky, 1979)) is the third category of Samuelson and Zeckhauser's explanations for status quo bias. It also manifests as the endowment effect (Thaler, 1980), in which people place more value on what they already have than of what they will or could obtain. In our research model, loss aversion is reflected in the path of switching costs to the user resistance to change. Since people are more sensitive to losing what they have (i.e. switching costs) than to gaining from adapting to new situations (i.e. switching benefits), switching costs may directly affect user resistance to change, in addition to its indirect effect via perceived value. This differs from Kim's (2011) model, which classifies loss aversion as another type of switching cost (i.e. loss cost).

In our research model, user experience was thought to moderate the relationship between user resistance to change and its antecedents (i.e. perceived value and the components of switching costs). Subgroup analysis (high versus low degree of user experience) was performed to test the moderation effect of user experience. Furthermore, it was presumed that the effect of user experience is reflected in all the factors that determine user resistance to change. An independent *t*-test was also conducted to examine the overall effect of user experience on user resistance.

Predicated on the conceptual framework drawn from the EIM and status quo bias research, we suggest the research model shown in Figure 1. Perceived value and three types of switching costs (i.e. uncertainty, transition, and sunk costs) were set as the antecedents of user resistance to change. Switching costs not only influence user resistance via perceived value, but also directly affect user resistance. The association of switching costs with user resistance is also moderated by user experience.

Formatted: Font: Times New Roman, Check spelling and grammar

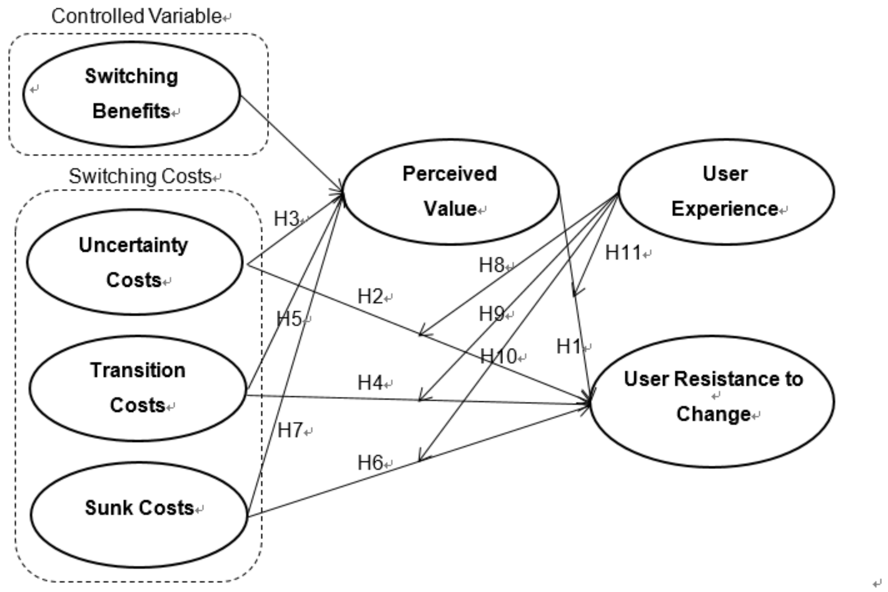

Figure 1. Research Model

Perceived value has been conceptualized as net benefits, on the basis of cost–benefit analysis (Kahneman & Tversky, 1979; Zeithaml, 1988). Modifying Kim and Kankanhalli's (2009) definition, we defined "perceived value" as the *perceived net benefits of change (i.e. switching benefits relative to switching costs) with respect to a new user interface*. In the context of an IVI system, perceived value will be determined by the benefits (e.g. convenience and usefulness) of using a new voice-based interface relative to its switching costs (e.g. uncertainty in a new situation and time and effort that users have made to familiarize themselves with a touch-based interface). Users tend to exhibit status quo bias and in turn resist change if the perceived value is low (i.e. the net benefit or equity is negative) (Joshi, 1991, 2005). Accordingly, we drew the following hypothesis.

H1: Perceived value negatively influences user resistance to change.

In line with Kim (2011), we defined "uncertainty costs" as the *perceptions of risk surrounding the performance of a new alternative* (i.e. a new user interface). Uncertainty is used as a term that includes well-defined probabilities (i.e. risk) and unknown or subjective probabilities of possible outcomes (i.e. ambiguity) (Einhorn & Hogarth, 1986). Inder and O'Brien (2003) argue that uncertainty induces users' negative psychological reactions; in this way, it adversely influences their valuation of alternatives and

Formatted: Font: Times New Roman, Check spelling and grammar

biases them towards the status quo, thus resulting in user resistance to change. Bhatnagar, Misra, & Rao (2000) have also shown that uncertainty costs (e.g. various risk factors) may affect perceived value associated with consumers' decision. Switching to a new way of working with a voice user interface could result in unexpected hassles or put users in unfamiliar driving situations in the context of an IVI system. Drawing upon the aforementioned early studies, we expect that these unanticipated situational elements are likely to be perceived by users as uncertainty costs, which may negatively affect the perceived value of using a new voice-based interface in an IVI system, and give rise to user resistance to change. We therefore hypothesized that:

H2: Uncertainty costs positively influence user resistance to change.
H3: Uncertainty costs negatively influence perceived value.

As also seen in the literature (Brockner et al., 1982; Kim, 2011; Samuelson & Zeckhauser, 1988), for our study, "transition costs" were defined as *irreversible investments, including time and effort*, *to adapt to new situations*, whereas "sunk costs" refer to *irreversible investments incurred in mastering the current way of working* (i.e. with a user interface). If substantial transition costs or sunk costs are incurred, such costs may induce status quo bias and hence user resistance to change (Polites & Karahanna, 2012; Samuelson & Zeckhauser, 1988). It has also been empirically shown that transition costs and sunk costs correlate with repurchase intentions (Jones et al., 2002). Logically, repurchase intentions positively correlate with user resistance to change. According to the EIM (Joshi, 1991; Kim, 2011), users perceive net values by making cost-benefit assessments of change, and in turn an increase in transition costs and sunk costs may lead to a decrease in perceived value. In the context of an IVI system, users are likely to perceive time and effort to switch to a new way of working with a voice user interface as transition costs, and consider time and effort that they have invested in the current way of working with a touch-based interface as sunk costs. These time and effort factors may adversely affect the perceived value of switching to a new voice user interface in an IVI system, and cause user resistance to change. Accordingly, we put forth the following hypotheses:

H4: Transition costs positively influence user resistance to change.
H5: Transition costs negatively influence perceived value.
H6: Sunk costs positively influence user resistance to change.
H7: Sunk costs negatively influence perceived value.

User experience is considered one of the critical factors to affect technology acceptance behaviors. Especially, much of the literature addresses (and subsequently finds) the moderating effect of user

Formatted: Font: Times New Roman, Check spelling and grammar

experience on the association of technology-related behavior with their predictor variables (e.g. perceived value) (Bhattacherjee & Premkumar, 2004; Castañeda et al., 2007; Gefen et al., 2003; Gupta & Kim, 2007; Rodgers, Negash, & Suk, 2005). Since user resistance to change highly correlates with technology acceptance behaviors, it is reasonable to assume that user experience also moderates the relationship between user resistance to change and its antecedents (e.g. perceived value and switching costs). Additionally, the relationship between switching costs and the behavior of users who stay with current products and services tends to be stronger when those users have a longer period of usage (Deng et al., 2010).

According to information processing theory, the accumulation of prior experience gives rise to an increase in the availability and accessibility of knowledge structures, learned and stored in memory, and thus highly experienced users can identify and use the most relevant information cues in their decision-making process. It is similar to the explanation on how experts better capture an important yet implicit information not apparent in the problem statement than novices (Chi, Glaser, & Rees, 1982). This implies that users with a higher degree of user experience are more likely to crystalize critical components of switching costs in their cognitive system, and this may in turn directly affect user resistance to change. Those who are less likely to spot crucial information cues due to their relatively low experience may rely upon the overall assessments of net benefits of change in IS.

The theory of planned behavior also suggests that a lack of information with respect to anticipated outcomes or unfamiliar situational elements may push users not to perform a certain behavior, via perceived behavioral control. In particular, users with a higher degree of prior experience are more likely to emphasize perceived behavioral control that has a strong impact on behavioral intention, while those with a lower degree of experience may focus more on the potential benefits of using IS (Taylor & Todd, 1995). Taking into consideration uncertain situational elements arising from using a voice user interface in an IVI system, not in other smart devices, users with relatively high experience can be more sensitive to potential loss of behavioral control, resulting in user resistance. These findings suggest that user experience may positively moderate the relationship between user resistance and uncertainty costs, given that control beliefs highly correlate with uncertainty costs.

Factoring in loss aversion, relatively high experienced users who have spent greater time and effort are more likely to resist a change than those with relatively low experience. This implies that user experience may positively moderate the relationship between user resistance and sunk costs. In contrast to uncertainty and sunk costs, the relationship between transition costs and user resistance can be negatively moderated by user resistance in that users who have been more frequently utilizing voice-based interfaces of other smart devices are likely to face less difficulty in switching from a touch-based interface to a voice user interface in an IVI system than those with less experience.

Formatted: Font: Times New Roman, Check spelling and grammar

Relatively low experienced users, who are less capable of identifying heuristic cues, may not sufficiently take information regarding control factors into account in the formation of their realistic expectations. They, in turn, tend to underestimate costs (e.g. uncertainty costs) and fixate on the potential benefits of using an information system (Taylor & Todd, 1995). This tendency is likely be reflected in the assessment of the overall value of switching an infotainment system. Those with relatively low experience are expected to be less sensitive to loss and more focus on perceived value in shaping realistic expectations that affect their behavioral intention and resistant behavior. In this regard, user experience may negatively moderate the relationship between user resistance and perceived value. Accordingly, we derived the following hypotheses.

H8: User experience positively moderates the relationship between uncertainty costs and user resistance to change.

H9: User experience negatively moderates the relationship between transition costs and user resistance to change.

H10: User experience positively moderates the relationship between sunk costs and user resistance to change.

H11: User experience negatively moderates the relationship between perceived value and user resistance to change.

Previous research on path dependency stresses that history does indeed matter (North, 1990; Sewell, 1996). By shaping self-reinforcing expectations, repeated past behaviors may generate a lock-in effect. Realistic expectations, formed through prior experience, also affect behavior intention and behavior (Taylor & Todd, 1995). In these ways, the influence of users' past experiences may extend to all the key variables in the model (i.e. user resistance to change, switching costs, and perceived value) (Ajzen, 1991). Moreover, if the effect of user experience goes beyond the antecedents included in the model (i.e. residual effects), such an effect could manifest in a measure of habit, and thus contribute to user resistance to change. Even if there is no strong residual effect, a high degree of repeated behavior may still lead to the development of realistic expectations on any change in behavior and self-reinforcing expectations, resulting in the lock-in effect and thus ensuring user resistance to change. Accordingly, users with a high degree of prior experience and those with a low degree would differ in terms of user resistance to change. From this, we drew the following hypothesis.

H12: User resistance to change differs between people with a high degree of user experience and those with a low degree.

Formatted: Font: Times New Roman, Check spelling and grammar

Prior research (Kim & Kankanhalli, 2009; Kim, 2011) suggests the mediation role of perceived value in the relationship between switching costs and user resistance. Indirect effects of switching costs, mediated by perceived value, on user resistance can be derived from hypotheses 1, 3, 5, and 7. Therefore, we assumed the following hypothesis.

> *H13: Perceived value partially mediates the relationship between switching costs and user resistance.*

IV. Research Methodology

A. Development of measurement instrument

In this study, we looked to rely upon previously validated scales and empirical procedures as much as possible. For *user resistance to change* (URC), Kim's (2011) measurement items were adopted and modified in a way to fit the context of this study. Measurement items for *perceived value* (PEC) were also adapted from Kim (2011), who used Sirdeshmukh, Singh, and Sabol's (2002) instrument for this construct. Following the previous measurement methods (Kim & Kankanhalli, 2009; Kim, 2011; Sirdeshmukh et al., 2002), scales for perceived value were designed to reflect the net benefits of switching the user interface, which can be measured by taking a comparative assessment of the costs and benefits of switching. For *uncertainty costs* (UNC), *transition costs* (TRI), *sunk costs* (SUN), and *switching benefits* (SWB), Kim's (2011) measurement items were also adopted and modified. (For *uncertainty costs*, *transition costs*, *and sunk costs*, Kim refers to Jones, Mothersbaugh, and Beatty (2002).) When instruments for *uncertainty costs* and *switching benefits* were modified in the context of an IVI system, we took into consideration Chang and Hsiao's (2011) scales.

With respect to *user experience*, the self-report measure of actual usage was used to operationalize the construct. The following question was asked to gauge respondents' user experience: "How many times do you use the voice user interface in other devices, such as smartphones and tablet computers, on a daily basis?" This question was intended to categorize survey respondents into two groups: people with a relatively low degree of user experience (LUX) with the voice user interface, and those with a relatively high degree of user experience (HUX). The boundary between the LUX and HUX groups was delineated by the criteria of the answer "zero": those who answered "zero" were grouped into the former group, while those who did not categorize themselves into the zero daily-usage group fell into the latter. The latter group wrote down any number above zero, or between zero and one. Since voice user interfaces in other smart devices have not yet heavily used in a daily basis, any number between zero and one—which means, for instance, one or two times usage per week—is still considered

Formatted: Font: Times New Roman, Check spelling and grammar

a relatively high degree of user experience that may allow those respondents to form heuristics and realistic expectations about a voice user interface. A few who wrote “sometimes”. We considered “sometimes” the same as any number between zero and one, and thus classified those respondents into the HUX group. Other than *user experience*, all the items were measured on a seven-point Likert scale, with 1 = entirely disagree and 7 = entirely agree. The survey instrument is shown in Appendix 1.

B. Data collection

For data collection, a survey was conducted both offline and online. The offline survey was conducted at a South Korean university. We collected a total of 200 responses, the majority of which were gathered via an in-person survey. Each respondent received a lottery ticket as a token of appreciation for survey participation. Those in their 20s accounted for 70% of the respondents. While the majority of the respondents were South Korean, the respondents were not restricted solely to South Koreans. The sample was skewed towards Asian people (particularly South Koreans) in their 20s. Nonetheless, the aim of this research was not to reproduce the distribution of demographic variables, but to explicate associations among constructs. This type of research may emphasize the relevance of sampling over representativeness (East & Uncles, 2008). South Korea is a country with one of the world’s highest smartphone penetration rates, and people in their 20s tend to drive the adoption of new technologies such as smartphones (Hakuhodo, 2013); these facts suggest that our sample is relevant in studying the factors that affect user resistance to change with respect to new smartphone interface-related technology. Since the survey focused on an IVI system—rather than the car itself—those with no driver’s license were not excluded from the survey. Table 1 presents the descriptive statistics of the respondents.

C. Control variable

In our research model, switching costs were the main predictor variable of user resistance to change, and perceived value served as a mediating variable. Yet, variation in perceived value cannot be explained solely by that in switching costs. Accordingly, switching benefits were included in the model as a control variable, as in the study by Kim (2011). It is of importance to determine whether there were any other possible effects unrelated to the hypothesized relationships in the model. We tested the effects of three demographic factors (i.e. *gender*, *age*, and *nationality*) as alternative predictors of user resistance, using SmartPLS. We found that the inclusion of those factors did not affect the testing results of the hypothesized relationships between the independent variables and the dependent variable. This indicated that the hypothesized relationships remained significant, even when demographic factors were controlled for.

Formatted: Font: Times New Roman, Check spelling and grammar

Table 1. Descriptive Statistics of the Respondents

Characteristic		Number (N = 200)	Percentage
Gender	Male	76	38.0
	Female	124	62.0
Age (years)	20–29	140	70.0
	30–39	48	24.0
	40–49	9	4.5
	Above 50	3	1.5
Nationality	Asian	157	78.5
	Others	43	21.5
User experience	Low	119	59.5
	High	81	40.5

V. Data Analysis and Results

A. *Instrument validation*

Drawing upon principal component analysis with varimax rotation, exploratory factor analysis (EFA) was first conducted. We extracted six factors with eigenvalues greater than 1.0 (see Appendix 2). The six factors cumulatively explained 76.32% of the total variance. All the measurement items were loaded into distinctively identified factors. Nonetheless, the factor-loading of *TRI3* was below 5, and its cross-loading was greater than 4. These results lead us to question the convergent and discriminant validities of the item. We conducted hypothesis testing with and without *TRI3* and found no significant difference in the test results; therefore, the results without dropping *TRI3* are hereafter reported. We also checked for possible common method bias, through the use of Harman's single-factor test. The fundamental assumption inherent in this test is that if common method variance exists, one general factor will account for the majority of the covariance in the independent variables (Podsakoff & Organ, 1986). No dominant factor emerged from the factor analysis (with the first factor explaining 37.08% of the variance), and so our data were not likely affected by common method bias.

Confirmatory factor analysis (CFA) was carried out to further assess convergent and discriminant validities. Data analysis was performed using component-based structural equation modeling (SEM) (i.e. partial least squares (PLS)). SmartPLS 2.0 was selected for use, as the research model in this study required a subgroup moderation test; this allowed us to undertake comparative analyses of groups whose sample size was less than 150. The PLS bootstrap approach to estimate the significance of the paths does not require parametric assumptions, and so it is suitable for the analysis

Formatted: Font: Times New Roman, Check spelling and grammar

of small data samples (Gefen, Straub, & Boudreau, 2000). We also used covariance-based SEM (i.e. LISREL) to confirm the PLS test results of the measurement model and structural model for main effects. The LISREL testing results showed that the model fit was, by and large, good,[2] and supported the PLS test results. For consistency of testing results between main effects and subgroup moderation effects, we decided in this study to report the PLS test results.

Convergent validity can be established when a validity test meets the following criteria (Gefen et al., 2000). First, the standardized path-loading needs to be both greater than 0.7 and statistically significant. Second, each of the composite reliability (CR) and the Cronbach's α of each construct needs to be greater than 0.7. Third, the average variance extracted (AVE) of each construct needs to be greater than 0.5. The results of our convergent validity test satisfied the aforementioned criteria, as shown in Table 2. All the standard path loadings were greater than 0.7 and statistically significant (*t*-value > 1.96). The CR and Cronbach's α of each construct exceeded 0.7, other than the Cronbach's α of *uncertainty costs* (0.65). (According to Nunnally (1978), for research purposes, a Cronbach's α value greater than 0.6 is still acceptable.) The AVE of each construct was also larger than 0.5. All in all, the convergent validity of the measurement instrument was supported.

Discriminant validity was examined by comparing the square root of AVE for each construct (diagonal term) with the correlations between the construct and other constructs (Fornell & Larcker, 1981). As shown in Table 2, all the square roots of AVE surpassed the correlations. Since some pair items (i.e. SWB–PEC, PEC–URC) showed correlations greater than 0.6, we conducted an additional discriminant validity test by drawing upon a constrained test, as suggested by Anderson and Gerbing (1988). The constrained test involves setting the correlation among pairs of variables to unity, and then examining the χ^2 difference between the original and constrained model. The constrained test results showed that the $\Delta\chi^2$ of the SWB–PEC and PEC–URC pairs—which were 166.60 and 300.11, respectively—were significant; this indicated that the original model was significantly better than the alternative models. This stands as evidence of discriminant validity.

Table 2. Results of Convergent Validity Test

Construct	**Std. loading of each item**				**AVE**	**CR**	**α**
User resistance to change (URC)	0.88	0.82	0.90	0.87	0.75	0.92	0.89
Switching benefits (SWB)	0.87	0.84	0.83	0.86	0.72	0.91	0.87
Perceived value (PEC)	0.92	0.93	0.89		0.83	0.94	0.90

[2] Normed χ^2 = 2.27, GFI = 0.85, AGFI = 0.80, NFI =0.93, CFI = 0.96, RMSEA = 0.080, standardized RMR = 0.085. Indications of good fit are: normed χ^2 < 3.0, GFI > 0.9, AGFI > 0.8, NFI > 0.9, CFI > 0.9, RMSEA < 0.08, RMR < 0.08 (Gefen et al., 2000; Hair, Anderson, Tatham, & Black, 1998; Hu & Bentler, 1999).

Formatted: Font: Times New Roman, Check spelling and grammar

Uncertainty costs (UNC)	0.73	0.70	0.86		0.59	0.81	0.65
Transition costs (TRI)	0.79	0.82	0.86		0.68	0.86	0.79
Sunk costs (SUN)	0.87	0.95	0.93		0.84	0.94	0.90

Table 3. Correlations among Latent Constructs

	Mean	**S.D.**	**PEC**	**SUN**	**SWB**	**TRI**	**UNC**	**URC**
PEC	4.90	1.11	**0.83**					
SUN	3.14	1.49	–0.02	**0.84**				
SWB	4.91	1.22	*0.68*	–0.07	**0.72**			
TRI	4.07	1.31	–0.31	0.38	–0.28	**0.68**		
UNC	4.27	1.03	–0.41	0.20	–0.33	0.43	**0.59**	
URC	2.95	1.25	*–0.62*	0.32	–0.54	0.55	0.47	**0.75**

Note: The highlighted diagonal figures (in bold) indicate the square root of AVE for each construct. S.D.: standard deviation. Construct abbreviations and their definitions are given in Table 2.

B. *Hypothesis testing*

The structural model was tested by applying a bootstrapping resampling technique with 200 cases, 500 bootstrap samples, and no sign-change option. As shown in Figure 2, the results of the main effects indicated that *perceived value* (H1), *uncertainty costs* (H2), *transition costs* (H4), and *sunk costs* (H6) have significant effects on *user resistance to change*, explaining 56% of its variance. Additionally, *uncertainty costs* (H3) have significant effects on *perceived value*. Nonetheless, the testing results did not support the hypotheses that *transition costs* (H5) and *sunk costs* (H7) have negative effects on *perceived value*. For the main effects testing, five hypotheses (H1, H2, H3, H4, and H6) were supported, whereas two hypotheses (H5 and H7) were rejected.

A multicollinearity test was conducted, as a few correlations exceeded 0.6. The most common approach in testing multicollinearity is to check variance influence factors (VIF) and the condition number (Mason & Perreault, 1991). The test showed that all VIF values were less than 5 and the condition numbers were lower than 30, thus indicating that multicollinearity was not likely to distort the test results of this study. Additionally, changes in R^2 values were explored to examine the effect, if any, of the mediating variable *perceived value* on the dependent variable *user resistance to change*. To this end, we calculated the effect size f^2, as suggested by Chin (1998).[3] The calculated f^2 effect size is

[3] i.e., $f^2 = (R^2_{included} - R^2_{excluded})/(1 - R^2_{included})$. See Chin (1998, p. 316).

Formatted: Font: Times New Roman, Check spelling and grammar

0.20, which is greater than 0.15 (i.e. medium effect; Cohen, 1988). This indicates that the model with the mediating variable is better than that which lacks it.

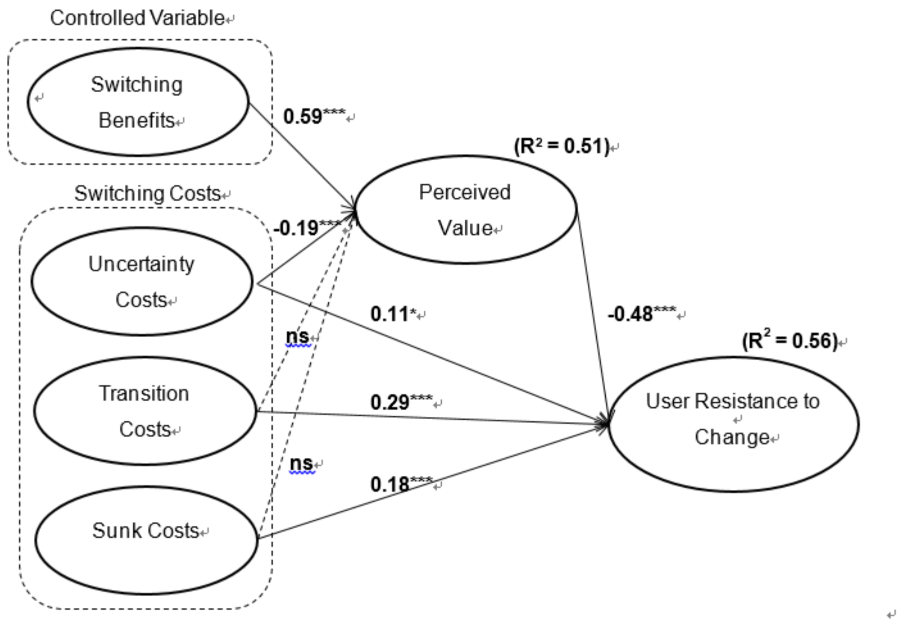

Figure 2. Structural Model for Main Effects

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; ns = not significant at the 5% significance level

For moderation hypotheses testing, subgroup analysis was undertaken to examine the moderating role of user experience, as suggested by Sharma, Durand, and Gur-Arie (1981). With this approach, the data were divided into two subgroups, on the basis of the hypothesized moderator *user experience*: the LUX group (N = 119) and the HUX group (N = 81). To examine the adequacy of our subgroups' sample sizes, Chin, Marcolin, and Newsted's (1996) requirement was first considered—that is, the sample size should be at least ten-fold greater than the number of items in the largest construct, or ten-fold greater than the largest number of structural paths directed at a particular construct in the structural model. In our model, *user resistance to change* was the largest construct (four items) and had the greatest number of paths (N = 4). This implies that 40 is the minimum sample size for our study. This is sufficiently satisfied by the sample size of our smaller subgroup (i.e. HUX, N = 81), which is also greater than 65 (i.e. the minimum sample size derived from Cohen's (1988) power analysis at the alpha level of 0.05 and the power level of 0.8, with a medium effect size of 0.2).

Formatted: Font: Times New Roman, Check spelling and grammar

Using SmartPLS 2.0, we conducted structure model testing on each subgroup, as shown in Figure 3. For the LUX group, *sunk costs*, *transition costs*, and *perceived value* each had significant effects on *user resistance to change*, while *uncertainty costs* did not. The total explained variance was 59%. For the HUX group, *uncertainty costs*, *transition costs*, and *perceived value* each had significant effects on *user resistance to change*, while *sunk costs* did not. This explained 61% of its variance. Following Gaskin's (2013) suggestion, we executed a parametric test to examine the statistical differences in path coefficients between the two subgroups, by leveraging the computation method of Chin (2000).[4] The calculated *t*-statistics were as follows: *perceived value* (4.348), *uncertainty costs* (3.155), *transition costs* (1.091), and *sunk costs* (0.678). Therefore, *user experience* had statistically significant effects on the relationship between *uncertainty costs* and *user resistance to change* (H8) and on the association between *perceived value* and *user resistance to change* (H11). Nonetheless, *user experience* had significant effects on neither the relationships between *transition costs* and *user resistance to change* (H9), nor on those between *sunk costs* and *user resistance to change* (H10).

The HUX group's path coefficient from *uncertainty costs* to *user resistance* (0.36) was greater than that of the LUX group (i.e. 0.02)—that is to say, *user experience* positively moderates the association of *uncertainty costs* with *user resistance to change* (H8). Also, the HUX group's path coefficient (absolute value) from *perceived value* to *user resistance* (0.17) was lower than that of the LUX group (i.e. 0.58). This means that *user experience* negatively moderates the relationship between *perceived value* and *user resistance* (H11). Figure 4 is a graphical representation of these moderating effects. In summary, for moderation effects testing, two hypotheses (H8 and H11) were supported and two hypotheses (H9 and H10) were rejected.

[4] The test statistic was computed as follows: $t = \frac{p_1 - p_2}{\left[\sqrt{\frac{(n_1-1)^2}{(n_1+n_2-2)} \times se_1{}^2 + \frac{(n_2-1)^2}{(n_1+n_2-2)} \times se_2{}^2}\right] \times \left[\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}\right]}$,

where the subgroup-specific path coefficients are denoted as p, the sample size as n, and the path coefficient standard errors resulting from bootstrapping as se.

Formatted: Font: Times New Roman, Check spelling and grammar

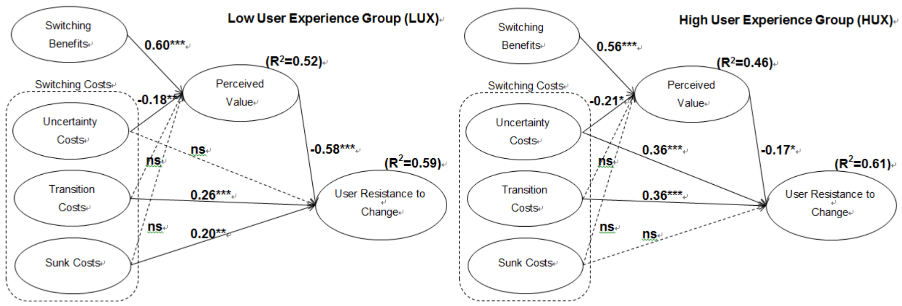

Figure 3. Structural Models for LUX and HUX Groups

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; ns = not significant at the 5% significance level

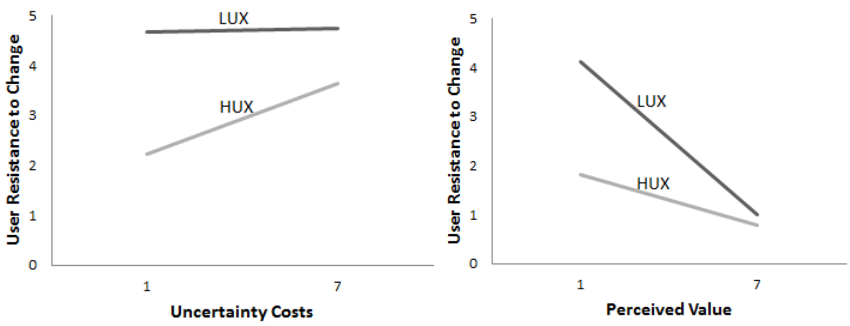

Figure 4. Graphical Representation of Moderating Effects

For H12, we conducted an independent *t*-test to examine whether the LUX and HUX groups were associated with a statistically significantly different mean *user resistance to change*. The LUX group was associated with URC $M = 3.09$ ($SD = 0.13$); in contrast, the HUX group was associated with URC $M = 2.74$ ($SD = 0.11$). The LUX and HUX groups' distributions were sufficiently normal for undertaking an independent *t*-test (i.e. the skewness/kurtosis statistic divided by its standard error is lower than 3.29 (Tabachnick & Fidell, 2007)), the results of which are shown in Table 4. The *t*-test results suggested a statistically significant effect ($t = 2.11$, $p < 0.05$; equal variances not assumed). Cohen's *d*/Hedge's *g* was estimated at 0.29 (that is, a moderate effect, according to the guidelines of Cohen (1992)). That is to say, the HUX group was associated with statistically significant lower mean *user resistance to change*, and this finding in turn supports H12.

Formatted: Font: Times New Roman, Check spelling and grammar

Table 4. Descriptive Statistics for LUX and HUX Group Distributions

	Mean	S.D.	Skewness	S.E. (Skew.)	Kurtosis	S.E. (Kurt.)
LUX	3.09	0.13	0.70	0.22	0.06	0.44
HUX	2.74	0.11	0.15	0.27	–0.36	0.53

For H13, we tested the mediating effects of perceived value on the relationship between switching costs and user resistance. We first examined the main effects of switching costs (i.e. uncertainty, transition and sunk costs) on user resistance in Model 1, and thereafter added perceived value, the mediator, to Model 2. We also tested the effects of switching costs on perceived value. Since the test results showed statistically insignificant effects of transition costs and sunk costs on perceived value, we focused on the indirect effect of uncertainty costs on user resistance to change, mediated through perceived value. As shown in Table 5, the path coefficient of uncertainty costs was dropped after adding perceived value, which indicates the partial mediation effect of perceived value for uncertainty costs. The Sobel test was also conducted to check the statistical significance of mediation effects (Sobel, 1982). For uncertainty costs, a decrease in the path coefficient from Model 1 (0.36) to Model (0.14) was significant at the 0.001 level (z = 3.32). This finding has shown that perceived value partially mediates the relationship between uncertainty costs and user resistance to change, which in part supports H13.

Table 5. The Mediating Effect of Perceived Value

Construct	**Model 1**	**Model 2**	**Sobel Test** (z-value)
Uncertainty costs	0.36***	0.14*	3.32***
Transition costs	0.32***	0.25***	ns
Sunk costs	0.11*	0.16***	ns
Perceived value		-0.56***	
R^2	0.35	0.55	

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; ns = not significant at the 5% significance level

VI. Discussion and Implications

A. Discussion of findings

Our major findings were as follows. The first notable finding was that uncertainty costs indirectly affect user resistance to change, via perceived value. We interpreted this finding in line with Joshi's (1991) EIM and Bhatnagar, Misra, and Rao's (2000) convenience–risk model. People consider risk a critical factor in the assessment of net benefits; uncertainty, in the context of our study, highly correlates with

Formatted: Font: Times New Roman, Check spelling and grammar

safety concerns that changing the user interface in an IVI system may affect users' driving performance and result in unexpected consequences. During the survey, some respondents mentioned that their experience of difficulties in controlling some of the functions of smart devices via the voice user interface had driven them to expect a similar experience (i.e. lack of control over an IVI system) in using voice control functionality. Those respondents raised safety concerns associated with the perceived risks. These perceived risks were translated into uncertainty costs, and, in turn, negatively influenced perceived value; this ultimately contributed to user resistance to change. The other two factors (i.e. transition and sunk costs), however, did not have indirect effects on user resistance. This means that the users did not perceive transition costs and sunk costs as critical factors in their net benefits assessment, in the context of switching from a touch-based interface to a voice user interface in an IVI system.

The second key finding was that user experience positively moderates the association between uncertainty costs and user resistance to change. The subgroup moderating effect showed that uncertainty costs more directly affect user resistance to change in the HUX group than in the LUX group. We interpreted this finding in accordance with informational processing theory (Bettman & Park, 1980; Gupta & Kim, 2007) and the theory of planned behavior (Ajzen, 1991; Taylor & Todd, 1995). Information processing theory predicts that users with more experience will identify the most relevant and important information through the use of heuristics, and rely on this information as heuristic cues during decision-making. According to the theory of planned behavior, on the other hand, users perceive less control over behavior when they anticipate obstacles or impediments; in turn, they may not perform a certain behavior. As stated, some survey respondents—particularly those with a high degree of user experience—raised safety concerns over the use of a voice user interface in an IVI system. This implied that some users with a higher degree of prior experience were able to anticipate possible obstacles or impediments in using the voice user interface in an IVI system, and use this information as heuristic cues in their decision to resist a change.

The third finding was that user experience negatively moderates the association of perceived value with user resistance to change. In accordance with the theory of planned behavior, people who face anticipated obstacles or impediments are likely to lower their realistic expectations with regard to behavior. Prior experience assumes a critical role in providing relevant information that affects perceived behavioral control (Bandura, 1986). This information can serve as a heuristic cue. We interpreted that users with a high degree of prior experience took into consideration control factors—such as the perceived difficulty of using a voice user interface in an IVI system—in the formation of their realistic perceived value. In contrast, the less-experienced group of participants discounted control information and placed more weight on perceived value.

Formatted: Font: Times New Roman, Check spelling and grammar

The fourth finding was that having a high degree of user experience with respect to voice user interfaces in other smart devices affects user resistance to change from the touch-based interface to the voice user interface in an IVI system. According to the *t*-test results, the HUX group showed statistically significantly low user resistance to change to the voice user interface, compared to the LUX group. This implies that having a high degree of user experience with voice user interfaces in other smart devices influences all the relevant factors that lock users into using voice user interfaces—even in an IVI system—by shaping expectations.

The fifth finding was, as the research model predicted, that three components of switching costs (i.e. uncertainty, transition, and sunk costs) and perceived value directly influence user resistance to change. These results were, by and large, consistent with the results of Kim's (2011) empirical test results, and they further support theoretical explanations based on status quo bias (Samuelson & Zeckhauser, 1988) and EIM (Joshi, 1991) for user resistance to change—even in the context of using a user interface in an IVI system, which differs from the implementation of enterprise systems.

B. Theoretical and practical implications

The results of this study provide several implications for academia and practice. First, our study investigated the interaction of user experience and switching costs with respect to user resistance to change. This objective highlights the salient contribution of this study—namely, the empirical testing of the moderating effects of user experience on the association between switching costs and user resistance to change. The literature suggests that the interplay of switching effects and inertia, formed in part through the accumulation of user experience, may affect user resistance to change (Barnes et al., 2004; Lai et al., 2011). Nonetheless, to the best of our knowledge, no research study has empirically examined the interaction of user experience with switching costs in relation to user resistance. This study's results indicate that user experience may strengthen the direct effects of switching costs—and of uncertainty costs in particular—and in turn weaken the indirect effects of switching costs via perceived value on user resistance. These empirical findings may add value to existing research on user resistance to change and switching costs.

Second, we empirically demonstrated the effects of switching costs and perceived value on user resistance to change—which are theoretically grounded in status quo bias research (Samuelson & Zeckhauser, 1988) and EIM (Joshi, 1991)—in the context of using a user interface in an IVI system. Previous research (Kim & Kankanhalli, 2009; Kim, 2011) tested the relationship between switching costs and user resistance to change with respect to the implementation of new enterprise systems. Further empirical testing of this research model in a different context would be considered a contribution.

Formatted: Font: Times New Roman, Check spelling and grammar

Through this empirical testing, we found that transition costs and sunk costs have no significant impact on perceived value.

The finding on the effect of sunk costs is relatively easily explainable. Sunk costs, by definition, are retrospective and irretrievable. Many economists believe that only prospective costs are relevant to a rational decision-making process. Although some (e.g. Mcafee, Mialon, & Mialon, 2010) contend that there are situations where it can be rational for people to base their behavior on sunk costs, their unconventional arguments are valid only to the extent that sunk costs are highly correlated with future costs and the probability of reaping benefits. In this light, the insignificant test result regarding the effect of sunk costs on perceived value can be interpreted as the following. Many users believe that previous investments of time and effort spent in learning how to familiarize themselves with a touch-based user interface do not significantly affect the prospective losses and the realization of expected gains of switching to a voice-based user interface in an IVI system. Hence, sunk costs are not factored in the rational decision-making process of assessing the overall value of switching a user interface. This is consistent with Kim's (2011) findings.

The effect of transition costs as found in our study differs from that seen in Kim (2011); this implies that the characteristics of uncertainty aversion and transition costs may differ among switching costs. Polites and Karahanna's (2012) research may shed light on the interpretation of this finding. They explained that two components of switching costs (i.e. sunk costs and transition costs) directly influence user resistance, and in turn such resistance, manifested as inertia, affects the perceived value of using a new system. They did not posit any indirect effect of sunk and transition costs on user resistance via perceived value, which is consistent with our study's finding. Interestingly, their research hypothesized a different causal direction between user resistance and perceived value from our study (i.e. user resistance → perceived value, not vice versa). This calls for future research on the clarification of a causal direction between user resistance and perceived value.

Third, the findings of this study send user interface developers—particularly, those who develop a voice user interface in an IVI system—the clear message that the careful design of a new user interface whose use demands less time and effort is of particular significance in alleviating user resistance to change. This practical implication is drawn from the finding of our study that among the direct effects of switching costs on user resistance, transition costs most strongly associate with user resistance to change. We also suggest that user interface developers seriously consider the potential risks associated with using a new user interface in various contexts, particularly at the stage at which the requirements of user interface functionality—which critically affect the benefits of using IS—are designed. This suggestion is proposed on the basis of the finding of this study that uncertainty costs (i.e. those that contain the risks that accompany the use of a new user interface) and switching benefits (e.g.

Formatted: Font: Times New Roman, Check spelling and grammar

quick access to services and the mitigation of cognitive workload while driving) jointly affect assessments of the overall value of switching to a voice user interface in an IVI system.

Fourth, we provide marketing strategists with the following implications, drawing on the findings of this research that user experience moderates the relationship between user resistance to change and its antecedents (i.e. perceived value and uncertainty costs). In order to target people with a low degree of user experience with voice user interfaces, it is advisable that firms develop advertisements that promote the overall benefits of user interfaces in an IVI system and stress the mitigation of uncertainty as part of the benefits of using a new user interface. In dealing with highly experienced users, marketing strategists should understand that those people are likely to continue to use a voice user interface, unless they perceive unexpected outcomes (e.g. safety concerns over driving performance). Hence, it is of importance to assure them that risks associated with using the voice user interface in a different context (i.e. an IVI system) can be effectively controlled and mitigated.

Our research findings also offer practical implications for firms that engage in platform and standards competition. In the fields of platform rivalry where network effects prevail, user lock-in strategies are essential to winning market share. As for user lock-in, interactions between switching costs and user experience are crucial determinants. The empirical test results of this study indicated that having a high degree of user experience with voice user interfaces in other smart devices can push users to lock themselves into other voice user interfaces, even in an IVI system. Nonetheless, our test results also suggested that those with a high degree of prior experience can have strong user resistance to change to voice user interfaces when they perceive uncertainty with regard to such change. The implications of these findings in the context of platform and standards competition are discussed in detail in the next section.

C. Reflections on platform and standards competition

The advancement of IT has been tearing down industrial “silos” and lending impetus to technological convergence. This has shifted the center of competition towards platforms and standards. Previously, in industries where standalone products were manufactured and distributed, large fixed costs-based economies of scale served as competitive edges, as they erected formidable entry barriers. Nonetheless, as products continue to evolve into complex systems that feature a multitude of modules, firms that govern platforms and interface standards (e.g. Apple and Google) have relentlessly enlarged the boundaries of their ecosystems and expanded into the domains of adjacent industries by bundling their own platform’s functionality with that of target products. This is also known as “platform envelopment” (Eisenmann, Parker, & Alstyne, 2011), and it is facilitated by strong network effects and shared user relationships.

Formatted: Font: Times New Roman, Check spelling and grammar

The distinctive feature of platform and standards-centric competition is the prominent role of "network effects" (Farrell & Saloner, 1986; Katz & Shapiro, 1985). These effects take the form of positive feedback loops that generate demand-side economies of scale, where the value of platform-mediated networks depends upon the number of users. Network effects can be potent, particularly when they manifest in the form of interface standards that define how complements connect to the platforms (Cusumano, 2010). Since the value of platforms is driven by the size of the user base, a user interface that is easy use—and therefore attracts more users—will emerge as a decisive factor in platform competition. Take graphical user interfaces (GUIs) as an example: Microsoft released Windows 95 with a substantially improved GUI that replaced the DOS command line interface, and this easy-to-use interface greatly contributed to Windows' domination of the personal computer platform market.

Capitalizing on the large user base-driven network effects and shared user relationships found in a multi-platform environment, Apple and Google have emerged as platform leaders who have entered several different markets. Cases in point are Apple's CarPlay and Google's Android Auto, both of which are found in the IVI system market. Recognizing the critical role of a user interface—something that is assumed in platform and standards competition—Apple and Google installed easy-to-use voice user interfaces in their IVI platforms. This ongoing phenomenon of platform envelopment highlights the significance of understanding users' behavioral factors as they often resist the use of a new user interface.

In this context, this study's findings shed light on platform and standards competition in two ways. First, we confirmed the extension of lock-in effects to the user interfaces found in a multi-platform environment. Once users grow accustomed to using one kind of user interface, they are highly likely to rely on the same type of interface, even in a dissimilar device. This tendency suggests that firms that can effectively control voice user interfaces—firms such as Apple and Google—will have the upper hand in cross-industry competition, compared to those that cannot. Second, our research findings showed that uncertainty engendered by the use of a new user interface in a different product may discontinue the user lock-in found in a multi-platform environment. An extremely high sensitivity to safety is a key difference between the product characteristics of cars and mobile phones; in this study, uncertainty regarding safety was reflected in the moderating effects of user experience on the interaction between switching costs and user resistance to change. This finding offers implications with regard to the defense strategies of existing firms that are concerned about growing platform envelopments. By accentuating the uncertainty spawned by heterogeneous product features, firms may defend themselves from platform envelopers that leverage new and easy-to-use user interfaces.

Formatted: Font: Times New Roman, Check spelling and grammar

D. Limitations

The results of this study should be interpreted with care. A large proportion of the survey respondents were aged 20–29 years, and so it was likely that some of these respondents did not have much driving experience. We did not control for driving experience as a variable, in that in the context of our study it was not a main determinant of user resistance. Nonetheless, we cannot completely rule out the possibility that some people's lack of driving experience may influence the test results. Notwithstanding, it is noteworthy that most of our findings are consistent with theoretical explanations and the results of previous empirical tests. We also examined the main effects and moderating effects without instruments that might be directly affected by driving experience (i.e. UNC2, SWB1), and found the same effects; this indirectly proved the robustness of the results.

This study featured a cross-sectional research design. A longitudinal research design may highlight the dynamics of user resistance to change over time, and therefore such a design is recommended in future research. Moreover, our research findings and their implications are based primarily on a specific user group (i.e. people in their 20s in South Korea); future research is needed to increase the generalizability of our findings and extend the discussion to other national or cultural groups.

VII. Conclusion

The voice user interfaces of in-vehicle infotainment (IVI) systems have recently drawn much attention, since through them, people can carry out the hands-free execution of services and applications while driving. In spite of the benefits that come with using a voice user interface, with mobile devices, a great number of people still heavily rely on touch-based user interfaces. This leads us to the reasonable expectation that with an IVI system, some portion of people will resist changing to a new user interface. User resistance to change has been extensively discussed as one of the main determinants of the success/failure of information systems (IS) implementation. In an attempt to contribute to the body of research on user resistance to change, our study examined the effects of switching costs and perceived value on user resistance; furthermore, it probed into the moderating effect of user experience on user resistance.

This study provided several findings and implications. First, we found that user experience positively moderates the association of uncertainty costs (one type of switching cost) with user resistance to change; it also negatively moderates the relationship between perceived value and user resistance to change. Second, this research empirically demonstrated that individuals with a high degree of prior experience with voice user interfaces in other smart devices tend to have low user resistance to

Formatted: Font: Times New Roman, Check spelling and grammar

change to a voice user interface, even in an IVI system. Third, we tested the impacts of switching costs and perceived value on user resistance to change, in the context of the user interface of an IVI system; this setting differs from those of previous research studies. Fourth, we pointed out that designing a user interface in a way that demands that users incur less time and effort in adapting to a new user interface is particularly important to mitigating user resistance. Fifth, it behooves user interface designers to take into consideration potential risks that come with using a new user interface in different contexts, especially in the development phase of identifying the functionality requirements of a user interface. Finally, we also suggested that marketing strategists execute advertising plans so as to reduce user resistance to change; such marketing could be segmented in terms of the degree of user experience.

These findings may cast some light on platform and standards rivalry, largely by illustrating the continuation of user lock-in across multiple platforms that share the same user interface, and its discontinuation triggered by heterogeneous product characteristics-grounded uncertainty. These reflections can be instrumental in devising strategies, among both platform leaders with easy-to-use user interfaces and defensive firms, both of whom engage in contemporary cross-industry competition. Future research could identify factors associated with uncertainty, and investigate interactions between those factors and the user experience with respect to user resistance. In the context of user interfaces, such research could also delve into the ways in which firms can “unlock” more-experienced users.

References

Abelson, R. P. (1976). Script processing in attitude formation and decision making. In J. S. Carroll & J. W. Payne (Eds.), *Cogniton and Social Behavior*. illsdale, NJ: Erlbaum.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211.

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, *103*(3), 411–423.

Arthur, W. B. (1994). *Increasing Returns and Path Dependence in the Economy*. University of Michigan Press.

Baldwin, C. Y., & Woodard, C. J. (2009). The architecture of platforms: A unified view. In *Platforms, Markets and Innovation* (pp. 19–44).

Bandura, A. (1986). *Social Foundations of Thought and Action: A Social Cognitive Theory*. Englewood Cliffs, NJ: Prentice-Hall.

Barnes, W., Gartland, M., & Stack, M. (2004). Old habits die hard: Path dependency and behavioral lock-in. *Journal of Economic Issues*, *38*(2), 371–377. Retrieved from http://www.jstor.org/stable/4228022

Bentler, P. M., & Speckart, G. (1979). Models of attitude-behavior relations. *Psychological Review*, *86*, 452–464.

Bettman, J. R., & Park, C. W. (1980). Effects of prior knowledge and experience and phase of the choice process on consumer decision processes: A protocol analysis. *Journal of Consumer Research*, *7*(3), 234–248.

Formatted: Font: Times New Roman, Check spelling and grammar

Bhatnagar, A., Misra, S., & Rao, H. R. (2000). On risk, convenience, and Internet shopping behavior. *Communications of the ACM*, *43*(11), 98–105. doi:10.1145/353360.353371

Bhattacherjee, A., & Premkumar, G. (2004). Understanding changes in belief and attitude toward information technology usage: A theoretical model and longitudinal test. *MIS Quarterly*, *28*(2), 229–254. Retrieved from http://www.jstor.org/stable/25148634

Brockner, J., Rubin, J. Z., Fine, J., Hamilton, T. P., Thomas, B., & Turetsky, B. (1982). Factors affecting entrapment in escalating conflicts: The importance of timing. *Journal of Research in Personality*, *16*(2), 247–266.

Burke, J. L., Prewett, M. S., Gray, A. A., Yang, L., Stilson, F. R., Coovert, M. D., … Redden, E. (2006). Comparing the effects of visual-auditory and visual-tactile feedback on user performance: a meta-analysis. In *Proceedings of the 8th international conference on Multimodal interfaces* (pp. 108–117). ACM.

Burnham, T. A., Frels, J. K., & Mahajan, V. (2003). Consumer switching costs: A typology, antecedents, and consequences. *Journal of the Academy of Marketing Science*, *31*(2), 109–126. doi:10.1177/0092070302250897

Castañeda, J. A., Muñoz-Leiva, F., & Luque, T. (2007). Web Acceptance Model (WAM): Moderating effects of user experience. *Information & Management*, *44*(4), 384–396. doi:10.1016/j.im.2007.02.003

Chaiken, S. (1980). Heuristic versus systematic information processing and the use of source versus message cues in persuasion. *Journal of Personality and Social Psychology*, *39*(5), 752–766. doi:10.1037//0022-3514.39.5.752

Chang, T., & Hsiao, W. (2011). Consumers' automotive purchase decisions: The significance of vehicle-based infotainment systems. *African Journal of Business Management*, *5*(11), 4152–4163. doi:10.5897/AJBM10.480

Chen, P. S., & Hitt, L. M. (2002). Study of the online brokerage industry measuring switching costs and the determinants of customer retention in Internet-enabled businesses: A study of the online brokerage industry. *Information Systems Research*, *13*(3), 255–274.

Chen, S., & Chaiken, S. (1999). The heuristic-systematic model in its broader context. In *Dual-process Theories in Social Psychology* (pp. 73–96).

Chi, M. T. H., Glaser, R., & Rees, E. (1982). Expertise in problem solving. In R. J. Sternberg (Ed.), *Advances in the Psychology of Human Intelligence, Vol. 1* (pp. 7–75). NJ: Erlbaum.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), *Modern Methods for Business Research* (pp. 295–336). London: Lawrence Erlbaum.

Chin, W. W. (2000). Frequently Asked Questions - Partial Least Sqaures & PLS-Graph. Retrieved December 23, 2014, from http://disc-nt.cba.uh.edu/chin/plsfaq.htm

Chin, W. W., Marcolin, B. L., & Newsted, P. R. (1996). A partial least squares latent variable modeling approach for measuring interaction effects: results from a Monte Carlo simulation study and voice mail emotion/adoption study. In J. I. DeGross, A. Srinivasan, & S. L. Jarvenpaa (Eds.), *Proceedings of the Seventeenth International Conference on Information Systems* (pp. 21–41). Cleveland, OH: Association for Information Systems.

Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). Lawrence Erlbaum Associates.

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*(1), 155–159.

Cusumano, M. (2010). Technology strategy and managemnet: The evolution of platform thinking. *Communications of the ACM*, *53*(1), 32–34. doi:10.1145/1629175.1629189

Formatted: Font: Times New Roman, Check spelling and grammar

David, P. A. (1985). Clio and the economics of QWERTY. *The American Economics Review*, *75*(2), 332–337.

Deng, Z., Lu, Y., Wei, K. K., & Zhang, J. (2010). Understanding customer satisfaction and loyalty: An empirical study of mobile instant messages in China. *International Journal of Information Management*, *30*(4), 289–300. doi:10.1016/j.ijinfomgt.2009.10.001

East, R., & Uncles, M. D. (2008). In praise of retrospective surveys. *Journal of Marketing Management*, *24*(9-10), 929–944. doi:10.1362/026725708X381975

Einhorn, H. J., & Hogarth, R. M. (1986). Decision making under ambiguity. *The Journal of Business*, *59*(4), S225–S250. Retrieved from http://link.springer.com/chapter/10.1007/978-94-009-4019-2_19

Eisenmann, T., Parker, G., & Alstyne, M. W. Van. (2006). Strategies for two-sided markets. *Harvard Business Review*, *84*(10). doi:10.1007/s00199-006-0114-6

Eisenmann, T., Parker, G., & Alstyne, M. W. Van. (2011). Platform envelopment. *Strategic Management Journal*, *32*, 1270–1285. doi:10.1002/smj

Evans, D. S. (2003). Some empirical aspects of multi-sided platform industries. *Review of Network Economics*, *2*(3), 191–209. doi:10.2202/1446-9022.1026

Farrell, J., & Saloner, G. (1986). Installed base and compatibility: Innovation, product preannouncements, and predation. *The American Economic Review*, *76*(5), 940–955. doi:10.2307/1816461

Farrell, J., & Shapiro, C. (1988). Dynamic competition with switching costs. *The RAND Journal of Economics*, *19*(1), 123–137. Retrieved from http://www.jstor.org/stable/2555402

Fornell, C., & Larcker, D. F. (1981). Evaluating strcutural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50.

Gaskin, J. (2013). *SmartPLS: Multigroup Moderation and Moderated Mediation*. Gaskination's Statistics. [Online]. Retrieved from http://www.youtube.com/watch?v=-BI8VweLQPc

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Inexperience and experience with online stores: The importance of TAM and trust. *IEEE Transactions on Engineering Management*, *50*(3), 307–321. doi:10.1109/TEM.2003.817277

Gefen, D., Straub, D., & Boudreau, M.-C. (2000). Structural equation modeling and regression: Guidelines for research practice. *Communications of the Association for Information Systems*, *4*.

GSMA Intelligence. (2014). *Mobile Platform Wars*.

Gupta, S., & Kim, H.-W. (2007). The moderating effect of transaction experience on the decision calculus in on-line repurchase. *International Journal of Electronic Commerce*, *12*(1), 127–158. doi:10.2753/JEC1086-4415120105

Hair, J. F. J., Anderson, R. E., Tatham, R. L., & Black, W. C. (1998). *Multivariate Data Analysis with Readings* (5th ed.). Prentice Hall.

Hakuhodo. (2013). Global HABIT.

Hayes-Roth, B. (1977). Evaluation of cognitive structures and processes. *Psychological Review*, *84*(May), 260–278.

Hirschheim, R., & Newman, M. (1988). Information systems and user resistance: Theory and practice. *The Computer Journal*, *31*(5), 398–408.

Howard, J. A. (1977). *Consumer Behavior: Application of Theory*. New York: Free Press.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. doi:10.1080/10705519909540118

Formatted: Font: Times New Roman, Check spelling and grammar

Inder, B., & O'Brien, T. (2003). The endowment effect and the role of uncertainty. *Bulletin of Economic Research*, *55*(3), 289–301.

Jackson, B. B. (1985). *Winning and Keeping Industrial Customers: The Dynamics of Customer Relationships.* Lexington, MA: Lexington Books.

Jones, M. A., Mothersbaugh, D., & Beatty, S. (2000). Switching barriers and repurchase intentions in services. *Journal of Retailing*, *76*(2), 259–274. doi:10.1016/S0022-4359(00)00024-5

Jones, M. A., Mothersbaugh, D. L., & Beatty, S. E. (2002). Why customers stay: Measuring the underlying dimensions of services switching costs and managing their differential strategic outcomes. *Journal of Business Research*, *55*(6), 441–450.

Joshi, K. (1991). A model of users' perspective on change: The case of information systems technology implementation. *MIS Quarterly*, *15*(2), 229–242.

Joshi, K. (2005). Understanding user resistance and acceptance during the implementation of an order management system: A case study using the equity implementation model. *Journal of Information Technology Case & Application Research*, *7*(1), 6–20. doi:10.1080/15228053.2005.10856057

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263–292.

Katz, M. L., & Shapiro, C. (1985). Network externalities, competition, and compatibility. *The American Economic Review*, *75*(3), 424–440.

Keil, M., Mann, J., & Rai, A. (2000). Why software projects escalate: An empirical analysis and test of four theoretical models. *MIS Quarterly*, *631-664*(24), 4.

Kenney, M., & Pon, B. (2011). Structuring the smartphone industry: Is the mobile Internet OS platform the key? *Journal of Industry, Competition and Trade*, *11*, 239–261. doi:10.1007/s10842-011-0105-6

Kessler, A. M., & Chen, B. X. (2015, February 22). Google and Apple Fight for the Car Dashboard. *The New York Times*. Retrieved from http://www.nytimes.com/2015/02/23/technology/rivals-google-and-apple-fight-for-the-dashboard.html?_r=1

Kim, H.-W. (2011). The effects of switching costs on user resistance to enterprise systems implementation. *IEEE Transactions on Engineering Management*, *58*(3), 471–482. doi:10.1109/TEM.2010.2089630

Kim, H.-W., & Kankanhalli, A. (2009). Investigating user resistance to information systems implementation: A status quo bias perspective. *MIS Quarterly*, *33*(3), 567–582.

Klemperer, P. (1987). Markets with consumer switching costs. *The Quarterly Journal of Economics*, (May). Retrieved from http://www.jstor.org/stable/1885068

Knight, F. H. (1921). *Risk, Uncertainty and Profit*. Houghton Mifflin Company.

Lai, L., Liu, C., & Lin, J. (2011). The moderating effects of switching costs and inertia on the customer satisfaction-retention link: auto liability insurance service in Taiwan. *Insurance Markets and …*, *2*(1), 69–78. Retrieved from http://businessperspectives.org/journals_free/imc/2011/IMC_2011_1_Lai.pdf

Lapointe, L., & Rivard, S. (2005). A multilevel model of resistance to information technology implementation. *MIS Quarterly*, *29*(3), 461–491.

Lin, T.-C., Huang, S.-L., & Hsu, C.-J. (2015). A dual-factor model of loyalty to IT product: The case of smartphones. *International Journal of Information Management*, *35*(2), 215–228. doi:10.1016/j.ijinfomgt.2015.01.001

Lucas, H. (1975). *Why Information Systems Fail*. New York: Columbia University Press.

Formatted: Font: Times New Roman, Check spelling and grammar

Lyytinen, K., & Hirschheim, R. (1987). Information systems failures: A survey and classification of the empirical literature. *Oxford Surveys in Information Technology*, *4*(1), 257–309.

Mangleburg, T. F., Sirgy, M. J., Grewal, D., Axsom, D., Hatzios, M., Claiborne, C. B., & Bogle, T. (1998). The moderating effect of prior experience in consumers' use of user-image baed versus utilitarian cues in brand attitude. *Journal of Business and Psychology*, *13*(1), 101–113.

Marakas, G. M., & Hornik, S. (1996). Passive resistance misuse: Overt support and covert recalcitrance in IS implementation. *European Journal of Information Systems*, *5*(3), 208–219.

Marks, L. J., & Olson, J. C. (1981). Towards a cognitive structure conceptualization of product famailiarity. In K. B. Monroe (Ed.), *Advances in Consumer Research* (pp. 145–150). Ann Arbor, MI: Association for Consumer Research.

Markus, M. L. (1983). Power, politics, and MIS implementation. *Communications of the ACM*, *26*(6), 430–444. Retrieved from http://dl.acm.org/citation.cfm?id=358148

Martinko, M. J., Zmud, R. W., & Henry, J. W. (1996). An attributional explanation of individual resistance to the introduction of information technologies in the workplace. *Behaviour & Information Technology*, *15*(5), 313–330. doi:10.1080/014492996120085a

Mason, C. H., & Perreault, W. D. (1991). Collinearity, power, and interpretation of multiple regression analysis. *Journal of Marketing Research*, *38*, 268–280.

Mcafee, R. P., Mialon, H. M., & Mialon, S. H. (2010). Do sunk costs matter? *Economic Inquiry*, *48*(2), 323–336. doi:10.1111/j.1465-7295.2008.00184.x

North, D. C. (1990). *Institutions, Institutional Change and Economic Performance*. Cambridge University Press.

Nunnally, J. C. (1978). *Psychometric Theory* (2nd ed.). New York: McGraw-Hill.

Oliver, R. L. (2010). *Satisfaction: A Behavioral Perspective on the Customer* (2nd ed.). Routledge.

Olson, J. C. (1977). Price as an informational cue: effects on product evaluations. In A. G. Woodside, J. N. Sheth, & P. D. Bennett (Eds.), *Consumer and Industrial Buying Behavior* (pp. 267–286). New York: North-Holland.

Pardo del Val, M., & Martínez Fuentes, C. (2003). Resistance to change: A literature review and empirical study. *Management Decision*, *41*(2), 148–155. doi:10.1108/00251740310457597

Park, C. W., & Lessig, V. P. (1981). Familiarity and its impact on consumer decision biases and heuristics. *Journal of Consumer Research*, *8*(2), 223–231.

Petty, R. E., & Cacioppo, J. T. (1986). *Communication and Persuasion: Central and Peripheral Routes to Attitude Change*. New York: Springer-Verlag.

Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. *Journal of Management*, *12*(4), 531–544.

Polites, G. L., & Karahanna, E. (2012). Shackled to the status quo: The inhibiting effects of incumbent system habit, switching costs, and inertia on new system acceptance. *MIS Quarterly*, *36*(1), 21–42.

Pon, B., Seppälä, T., & Kenney, M. (2014). Android and the demise of operating system-based power: Firm strategy and platform control in the post-PC world. *Telecommunications Policy*, *38*(11), 979–991. doi:10.1016/j.telpol.2014.05.001

Porter, M. E. (1980). *Competitive Strategy: Techniques for Analyzing Industries and Competitors*. New York: Free Press.

Rao, A. R., & Monroe, K. B. (1988). The moderating effect of prior knowledge on cue utilization in product evaluations. *Journal of Consumer Research*, *15*(2), 253–264.

Formatted: Font: Times New Roman, Check spelling and grammar

Rochet, J., & Tirole, J. (2003). Platform competition in two-sided markets. *Journal of the European Economic Association*, *1*(4), 990–1029.

Rodgers, W., Negash, S., & Suk, K. (2005). The moderating effect of on-line experience on the antecedents and consequences of on-line satisfaction. *Psychology and Marketing*, *22*(4), 313–331. doi:10.1002/mar.20061

Rumelt, R. P. (1995). Inertia and transformation. In C. A. Montgomery (Ed.), *Resource-based and Evolutionary Theories of the Firm* (pp. 101–32). MA: Kluwer Academic Publishers.

Samuelson, W., & Zeckhauser, R. (1988). Status quo bias in decision making. *Journal of Risk and Uncertainty*, *1*(1), 7–59.

Schmidt, E. (2011). *Hearing on "The Power of Google: Serving Consumers or Threatening Competition?"* The Senate Committee on the Judiciary Subcommittee on Antitrust, Competition Policy, and Consumer Rights. Retrieved from https://drive.google.com/file/d/0B5JQZrEEQaEONDJkZWI1MzUtMzk5Mi00ZDRhLWIyZmMtMWRkOWU1MmU5ZmZk/view

Sewell, W. H. (1996). Three temporalities: Toward an eventful sociology. In T. J. McDonald (Ed.), *The Historic Turn in the Human Sciences* (pp. 245–280). The University of Michigan Press.

Sharma, S., Durand, R., & Gur-Arie, O. (1981). Identification and analysis of moderator variables. *Journal of Marketing Research*, *18*, 291–300. Retrieved from http://www.jstor.org/stable/3150970

Sheppard, B., Hartwick, J., & Warshaw, P. (1988). The theory of reasoned action: A meta analysis of past research with recommendations for modifications and future research. *Journal of Consumer Research*, *15*(3), 325–343.

Sirdeshmukh, D., Singh, J., & Sabol, B. (2002). Consumer trust, value and loyalty in relational exchange. *Journal of Marketing*, *66*(1), 15–37.

Sobel, M. (1982). Asymptotic confidence intervals for indirect effects in structural equation models. *Socialogical Methodology*, *13*(1982), 290–312.

Stotland, E., & Canon, L. K. (1972). *Social Psychology: A Cognitive Approach*. Philadelphia, PA: Saunders.

Tabachnick, B. G., & Fidell, L. G. (2007). *Using Multivariate Statistics*. Needham Heights, MA: Allyn & Bacon.

Taylor, S., & Todd, P. (1995). Assessing IT usage: The role of prior experience. *Management Information Systems Quarterly*, *19*(4), 561–570. doi:10.2307/249633

Thaler, R. (1980). Toward a positive theory of consumer choice. *Journal of Economic Behavior & Organization*, *1*, 39–60.

Wegener, D. T., Petty, R. E., Blankenship, K. L., & Detweiler-Bedell, B. (2010). Elaboration and numerical anchoring: Implications of attitude theories for consumer judgment and decision making. *Journal of Consumer Psychology*, *20*(1), 5–16. doi:10.1016/j.jcps.2009.12.003

Weiss, A. M., & Anderson, E. (1992). Converting from independent to employee salesforces: The role of perceived switching costs. *Journal of Marketing Research*, *29*(1), 101–115.

West, J., & Mace, M. (2010). Browsing as the killer app: Explaining the rapid success of Apple's iPhone. *Telecommunications Policy*, *34*(5-6), 270–286. doi:10.1016/j.telpol.2009.12.002

Whitten, D., & Wakefield, R. L. (2006). Measuring switching costs in IT outsourcing services. *The Journal of Strategic Information Systems*, *15*(3), 219–248. doi:10.1016/j.jsis.2005.11.002

Formatted: Font: Times New Roman, Check spelling and grammar

Wood, W., & Kallgren, C. A. (1988). Communicator attributes and persuasion: Recipients' access to attitude-relevant information in memory. *Personality and Social Psychology Bulletin*, *14*, 172–182.

Yang, Z., & Peterson, R. T. (2004). Customer perceived value, satisfaction, and loyalty: The role of switching costs. *Psychology and Marketing*, *21*(10), 799–822. doi:10.1002/mar.20030

Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: a means-end model and synthesis of evidence. *The Journal of Marketing*, *52*(3), 2–22.

Zeithaml, V. A., Parasuraman, A., & Berry, L. L. (1985). Problems and strategies in services marketing. *The Journal of Marketing*, *49*(2), 33–46.

Formatted: Font: Times New Roman, Check spelling and grammar

Appendix 1. Measurement Instrument

Construct	Item	Wording	Reference
User resistance to change	URC1	I would not comply with the change associated with a new way of working with a voice user interface in an in-vehicle infotainment system.	Kim (2011)
	URC2	I would not spend time and effort coping with the change associated with a new way of working with a voice user interface in an in-vehicle infotainment system.	
	URC3	I oppose the change associated with a new way of working with a voice user interface in an in-vehicle infotainment system.	
	URC4	I would resist the change to a new way of working with a voice user interface in an in-vehicle infotainment system.	
Perceived value	PEC1	Considering the switching benefits and costs of the new system, the change associated with a new way of working with a voice user interface in an in-vehicle infotainment system would deliver me good value.	Kim (2011), Sirdeshmukh et al. (2002)
	PEC2	Considering the convenience and usefulness of the voice user interface, the change associated with a new way of working with a voice user interface in an in-vehicle infotainment system is beneficial to me.	
	PEC3	Considering uncertainty in a new situation and investments that I have made in the status quo, the change associated with a new way of working with a voice user interface in an in-vehicle infotainment system is of good value.	
Uncertainty costs	UNC1	Switching to a new way of working with a voice user interface in an in-vehicle infotainment system could result in unexpected hassles.	Kim (2011), Jones et al. (2002), Chang and Hsiao (2011)
	UNC2	I am not sure how my driving performance would be affected if I were to switch to a new way of working with a voice user interface in an in-vehicle infotainment system.	
	UNC3	If I were to switch to a new way of working with a voice user interface in a vehicle infotainment system, the driving situations I would face would be uncertain.	
Transition costs	TRI1	It would take a lot of time and effort to switch to a new way of working with a voice user interface in an in-vehicle infotainment system.	Kim (2011), Jones et al. (2002)
	TRI2	The costs in time and effort to switch to a new way of working with a voice user interface in a vehicle infotainment system are high.	
	TRI3	It would be a hassle for me if I were to adapt to a new way of working with a voice user interface in an in-vehicle infotainment system.	
Sunk costs	SUN1	I have already put a lot of time and effort into the current way of working with a touch-based user interface.	Kim (2011), Jones et al. (2002)
	SUN2	A lot of time and effort has gone into learning and becoming proficient with the current way of working with a touch-based user interface.	
	SUN3	I made a significant investment in learning and becoming proficient with the current way of working with a touch-based user interface.	
Switching benefits	SWB1	Changing to a new way of working with a voice user interface in a vehicle infotainment system would enhance my driving performance more than the current touch-based system.	Kim (2011), Chang & Hsiao (2011)
	SWB2	Changing to a new way of working with a voice user interface would enable me to execute the applications in a vehicle infotainment system easier than the current touch-based system.	
	SWB3	Changing to a new way of working with a voice user interface would enable me to execute the applications in an in-vehicle infotainment system more quickly than the current touch-based system.	
	SWB4	Changing to a new way of working with a voice user interface in an in-vehicle infotainment system would improve the quality of driving experience more than the current touch-based system.	

Formatted: Font: Times New Roman, Check spelling and grammar

User experience	EX	How many times do you use a voice user interface in other devices, such as smartphones and tablet computers, on a daily basis?

Appendix 2. Results of Exploratory Factor Analysis

Construct	**Item**	**Component**					
		URC	**SWB**	**SUN**	**PEC**	**TRI**	**UNC**
User resistance to change	URC3	**0.80**	–0.27	0.10	–0.21	0.12	0.16
	URC4	**0.78**	–0.20	0.11	–0.21	0.11	0.19
	URC1	**0.76**	–0.24	0.24	–0.26	0.10	0.09
	URC2	**0.74**	–0.08	0.13	–0.21	0.20	0.12
Switching benefits	SWB2	–0.16	**0.88**	0.03	0.08	0.02	–0.07
	SWB3	–0.09	**0.80**	–0.03	0.25	–0.13	–0.12
	SWB1	–0.27	**0.74**	–0.04	0.29	–0.08	–0.08
	SWB4	–0.32	**0.67**	–0.03	0.39	0.07	–0.06
Sunk costs	SUN2	0.14	0.02	**0.93**	–0.02	0.10	0.10
	SUN3	0.15	0.03	**0.91**	0.00	0.11	0.05
	SUN1	0.11	–0.07	**0.84**	0.07	0.18	0.07
Perceived value	PEC2	–0.26	0.34	0.05	**0.82**	–0.04	–0.14
	PEC1	–0.31	0.27	–0.01	**0.80**	–0.09	–0.17
	PEC3	–0.33	0.38	0.07	**0.69**	–0.01	–0.15
Transition costs	TRI2	0.20	0.07	0.16	–0.13	**0.89**	0.07
	TRI1	0.12	–0.11	0.20	0.04	**0.88**	0.06
	TRI3	*0.48*	–0.21	0.17	–0.08	*0.44*	0.30
Uncertainty costs	UNC2	0.04	–0.05	0.16	–0.15	–0.04	**0.78**
	UNC3	0.27	–0.13	0.07	–0.23	0.04	**0.70**
	UNC1	0.21	–0.10	–0.05	0.04	0.37	**0.67**
Rotation sums of eigenvalues		3.32	3.03	2.63	2.39	2.06	1.84
% of Variance		16.60	15.15	13.15	11.93	10.31	9.19
Cumulative %		16.60	31.75	44.90	56.83	67.14	76.32

Extraction method: principal component analysis; rotation method: varimax with Kaiser normalization.

Formatted: Font: Times New Roman, Check spelling and grammar