Complexity of In-Vehicle Controllers and Their Effect on Task Performance

Seul Chan Lee & Yong Gu Ji

To cite this article: Seul Chan Lee & Yong Gu Ji (2018): Complexity of In-Vehicle Controllers and Their Effect on Task Performance, International Journal of Human–Computer Interaction, DOI: 10.1080/10447318.2018.1428263

To link to this article: https://doi.org/10.1080/10447318.2018.1428263

Published online: 19 Jan 2018.
Complexity of In-Vehicle Controllers and Their Effect on Task Performance

Seul Chan Lee and Yong Gu Ji

Department of Industrial Engineering, Yonsei University, Seoul, Korea

ABSTRACT
Smart functions in vehicles have led to an increase in the complexity of control interfaces. This study aims to develop a model for evaluating in-vehicle controller complexity and to investigate the relationship between complexity and task performance. A research framework consisting of three complexity dimensions (functional, behavioral, and structural dimensions) and controller-related variables was developed based on previous literature. A user experiment was conducted using 10 vehicles and 91 participants. A regression analysis was used to examine the relationship between the measurement variables and perceived controller complexity, and the results indicated correlations between them. An increase in functional dimension variables caused an increase in the perceived complexity level, while behavioral dimension variables are not a statistically significant predictor. Structural dimension variables showed different results depending on the characteristics of the variables. The results of the control task experiment showed a negative correlation between task performance and the perceived complexity level. In addition, satisfaction decreased with increasing levels of complexity. These results provide insights for managing in-vehicle controller complexity.

1. Introduction

Owing to developments in information and network technologies, vehicle systems have become smart enough to provide numerous convenient functions for drivers such as in-vehicle information systems. While these functions are convenient, there are apparent downsides such as the increasing complexity of in-vehicle interfaces (Hwangbo, Lee, & Ji, 2016). In particular, many physical controllers and interface components are used to operate in-vehicle information systems, resulting in increased cognitive demands on drivers to perform both driving- and nondriving-related tasks. This phenomenon inevitably has negative effects on driving performance (Dukic, Hanson, & Falkmer, 2006; Dukic, Hanson, Holmqvist, & Wartenberg, 2005; Lee, Roberts, Hoffman, & Angell, 2012; Mitsopoulos-Rubens, Trotter, & Lenné, 2011; Reed & Green, 1999). Although it is recognized that increasing complexity will create negative effects on driving safety, few studies have been conducted to evaluate controller complexity. In addition, several limitations exist in the evaluation of in-vehicle controller complexity in previous studies. First, researchers typically focused on individual interface design factors. Although the results of these evaluations are informative, the complexity needs to be evaluated from a holistic point of view, as multiple design factors are inevitably interrelated. Second, few studies have attempted to determine the relationship between interface design variables and subjective evaluations in vehicle environments. Hence, we developed a statistical model for evaluating the complexity of in-vehicle interfaces and examined the relationship between perceived controller complexity and task performance by human operators.

In the following section, we review related studies. Based on these reviews, we derive a measurement framework to predict interface controller complexity and explain the data collection process used to build research models. Next, we present the results on the validity and reliability of the developed model and investigate the effects of controller complexity on task performance. Finally, we discuss our results and present the conclusions.

2. Related studies

2.1. In-vehicle interface evaluation

Considering physical interface components during the development process of a new vehicle is important, as they significantly affect usability and user experience. Therefore, researchers have extensively studied and evaluated system interfaces ranging from small and simple devices (Colle & Hiszem, 2004; Hancock, Sawyer, & Stafford, 2015; Heo, Ham, Park, Song, & Yoon, 2013; Jin & Ji, 2010; Lee, Cha, Hwangbo, Mo, & Ji, 2018) to large and complex systems (dos Santos, Teixeira, Ferraz, & Carvalho, 2008; Harvey, Stanton, Pickering, McDonald, & Zheng, 2011). In particular, user-centered design methods such as heuristics, user tests, and interviews have been widely used for evaluating the interfaces. In the case of small devices
(e.g., smartphones), testing the effects of interface components or form factors using prototypes or mock-ups is relatively easy. However, adapting these methods to large and complex interfaces is difficult. Accordingly, researchers usually use dual-task methods to examine the effects of interface design components (Large et al., 2016; Oh, Ko, & Ji, 2016; Wittmann et al., 2006). These approaches are effective and important because the performance of the primary task is closely related to driving safety. Though we can examine the effects of individual variables and design interfaces based on the results of the studies on individual variables, we cannot ignore the additional effects of interactions between the variables that may lead to unexpected outcomes.

Quantitative modeling methods make up for these drawbacks, helping researchers evaluate the effects of more than two variables and compare different systems. In addition, detecting changes based on variable levels is relatively easy. Hence, numerous studies have used quantitative modeling methods based on measurable parameters to evaluate human behavior or the perception of interface components in vehicle environments, such as satisfaction (You, Ryu, Oh, Yun, & Kim, 2006), visual complexity (Lee, Hwangbo, & Ji, 2016; Ling, Lopez, & Shehab, 2013; Yoon, Lim, & Ji, 2015a, 2015b), and driver posture (Park, Ebert, Reed, & Hallman, 2015, 2016; Reed, Manary, Flannagan, & Schneider, 2002). In this study, we developed and validated a quantitative model to evaluate in-vehicle controller complexity.

### 2.2. Complexity studies in human factors

Several categories of complexity studies have been conducted in the fields of human factors and human–systems interactions (Ham, Park, & Jung, 2011), and they can be classified as theoretical and practical studies. The former includes studies that deal with complexity definitions, complexity types, and factors affecting complexity, while the latter focuses on complexity-based designs, complexity measurements and quantification, as well as the interrelationship between complexity and human performance. Each topic is related to the others; for instance, the complexity factors are selected based on the definition of complexity. These factors provide basic conceptual information on complexity-based design, quantitative research, and human performance studies.

Generally, there are several different definitions of complexity, and they are based on important characteristics that are related to specific areas of interest, as it is difficult to define complexity in a single sentence (Liu & Li, 2012). Regarding human factors, definitions vary according to the focus of the interactions between humans and systems (Ham et al., 2011), and various complexity types can be defined. For example, Li and Wieringa (2000) classified complexity into objective and subjective complexity. Objective complexity is based on technically designed characteristics or situation-oriented factors such as task complexity, process complexity, and human–machine interface (HMI) complexity. Subjective complexity refers to how human operators subjectively perceive and are aware of the levels of complexity, such as perceived complexity. It is also possible to classify complexity on the basis of the characteristics of the targets into non-behavioral complexity and behavioral complexity (Henneman & Rouse, 1986). Research on non-behavioral complexity has traditionally focused on the state of specific systems such as computational complexity, software complexity, and physical system complexity, while studies on behavioral complexity have attempted to address psychological and behavioral issues, including perceptual, cognitive, and action complexity.

According to these definitions and types of complexity, various factors have been selected. Kemps (Kemps, 1999) and Yoon (Yoon et al., 2015a) selected quantitative attributes and structural attributes as the significant factors affecting visual complexity. In general, quantitative factors have a positive correlation with complexity, and negative correlations were found between complexity and structural factors. Xing (2007) defined information complexity in air traffic control displays as a combination of three basic factors (size, variety, and rules) and three stages of information processing (perception, cognition, and action), and nine metrics were proposed based on combinations of these stages. Lee et al. (2016) attempted to explain the relationship between perceived visual complexity and three factors: quantity, variety, and relation. Although complexity-related topics have been actively studied and discussed, few studies have been conducted on practical topics. Moreover, these studies usually focus on visual complexity or task complexity. In other words, studying the complexity of physical user interfaces is necessary, particularly for in-vehicle controller interfaces.

### 2.3. Deriving interface design variables for developing controller complexity

To evaluate in-vehicle controller complexity, we should analyze the interface features in terms of system purpose. It is necessary to structure the situations faced by users due to the presence of a large number of devices and large amount of information (Rasmussen, 1985). Therefore, Rasmussen (1985) divided the functional aspects of systems according to their means and ends based on abstraction hierarchy. Lower levels of abstraction are accorded to physical aspects, and higher levels of abstraction are related to a system’s purpose. This viewpoint is similar to that of Gero (Gero, 1990; Gero & Kannengiesser, 2004), who explained the design process based on the function–behavior–structure (FBS) framework. The function is the purpose of the design, that is, its teleology. The behavior refers to attributes derivable from a structure or expected from a structure, and the structure refers to the elements of an artifact and their interrelationships. The FBS framework compares the expected behavior of a system interface and its structure; this process transforms a system structure into a description. It is confirmed that the FBS framework is useful for analyzing not only user interfaces but also the complexity structurally (Ham, Park, & Jung, 2012; Lin & Zhang, 2005).

We defined the functional, behavioral, and structural components needed to analyze the complexity of in-vehicle controllers. The functional complexity component comprises interface design variables related to a variety of functions, the behavior complexity component characterizes the interface design variables affecting the behavior of a human operator,
and the structural complexity component includes the basic physical user interface design variables. Based on the FBS framework, we selected interface design variables related to in-vehicle controller complexity by reviewing previous studies (Cummings, Sasangohar, Thornburg, Xing & D’Agostino, 2010; Kang & Seong, 1998; Li & Wieringa, 2000; Murata, Yamada, & Moriwaka, 2009). Interface design variables are important in that they explain the human perception of in-vehicle controller complexity. Thus, we selected and defined each interface design variable for developing a statistical complexity model. The list and definitions of the variables are presented in Table 1.

3. Methodology
3.1. Research framework
To assess the complexity of in-vehicle controllers, we developed and verified a research model. We collected and selected in-vehicle interface design variables as an independent variable for developing the complexity model based on previous studies. The collection and measurement of these variables was done by our research team. Participants in the study evaluated the complexity score for each vehicle, and these scores were used as dependent variables of the model. The participants performed the control task in this process and conducted the evaluation based on their experience. We built a statistical model based on the data obtained. The validity of the developed model was verified by analyzing the correlation between the performances of the control tasks.

3.2. Experimental design
Participants: We recruited 92 participants (male = 41 and female = 51) aged 20 to 71 years (Mean = 43.56, SD = 12.50). We recruited participants through an online advertisement website. All participants were required to have a valid driver’s license and their own or family-owned vehicles that they drove regularly. Those who had a driver’s license but did not drive on a regular basis were excluded. All participants did not have any visual difficulties during the driving process and had no inconvenience in freely moving their hands to perform the control task. In addition, we rejected several people unfamiliar with the operation of the vehicles, for example, someone who could not start an engine or did not know the basic functions of in-vehicle buttons.

Apparatus: We recruited the actual vehicles considering following criteria. First, the brands of vehicles were limited to domestic manufacturers, as we doubted that brand image would influence the results. Second, we considered the vehicles with a variety of in-vehicle controller and interface configurations. As a result, we used 10 different actual vehicles: two compact vehicles, two sport utility vehicles, and six sedans. All vehicles used for the experiment were parked at the Yonsei University.

Tasks: To investigate the perceived controller complexity, we required participants to perform tasks using in-vehicle controllers (Figure 1). These tasks were organized based on past research (Harvey et al., 2011; Pfleging, Schneegass, & Schmidt, 2012; Young & Salmon, 2012) and involved typical functions present in all vehicles.

<table>
<thead>
<tr>
<th>Objective measurement variables.</th>
<th>Functional dimension</th>
<th>Behavioral dimension</th>
<th>Structural dimension</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variables</td>
<td>No. of single task controllers</td>
<td>Number of controllers used for a single task (or single mode).</td>
<td>Number of controllers used for more than two tasks (or two modes)</td>
</tr>
<tr>
<td></td>
<td>No. of multitask controllers</td>
<td>Number of controllers that make state changes within one condition (e.g., on/off).</td>
<td>Number of controllers that make state changes within continuous conditions (e.g., radio frequency change)</td>
</tr>
<tr>
<td></td>
<td>No. of nominal controllers</td>
<td>No. of continuous interval controllers</td>
<td>No. of indicator lamps</td>
</tr>
<tr>
<td></td>
<td>No. of controller groups</td>
<td></td>
<td>Number of lamps that indicate whether a function is activated</td>
</tr>
<tr>
<td></td>
<td>No. of controllers per group</td>
<td>Ratio of controllers in group</td>
<td>Average number of controllers per group</td>
</tr>
<tr>
<td></td>
<td>Overlapped controllers</td>
<td></td>
<td>Ratio of the number of controllers within a group to the number of controllers without a group</td>
</tr>
<tr>
<td></td>
<td>Size of controller</td>
<td></td>
<td>Number of controllers that overlap with each other</td>
</tr>
<tr>
<td></td>
<td>Distance between SW edge and SW buttons</td>
<td></td>
<td>Average size of controllers</td>
</tr>
<tr>
<td></td>
<td>No. of dummy controllers</td>
<td></td>
<td>Average distance from steering wheel edge to controllers that are situated in steering wheel</td>
</tr>
</tbody>
</table>

Note. SW: steering wheel
Accordingly, two types of tasks were performed by the participants for the experiment. Infotainment tasks included turning on/off the power of the audio system, changing between FM/AM modes, tuning the radio frequency, controlling the volume, and changing the audio/CD play mode. Air conditioning-related tasks included turning on/off frost protection of the front/rear windshield glass, changing the air-circulation mode, controlling the temperature, and controlling the air volume.

The participants were required to perform the in-vehicle control task in actual vehicle settings. However, they did not perform the driving task and only performed in-vehicle control tasks. The reason why we did not consider the test condition along with the driving task is as follows. According to Green (1999), in-vehicle system interfaces can be adequately assessed even in a stationary situation, where all tasks should be done within 15 s. In addition, we wanted the participants to evaluate the controller complexity of the interface itself without being affected by the driving tasks, which result in high workload or distraction. In actuality, the studies cited below showed meaningful findings relying on simple tasks, without considering the actual task context, when determining the influence of interface components on the perception of complexity (Lee et al., 2016; Tuch, Bargas-Avila, Opwis, & Wilhelm, 2009).

3.3. Procedure

First, the experiment moderator explained the overall procedure of the experiment. Before beginning the experiment, the participants filled out a written form giving informed consent and providing demographic information pertaining to their age, gender, and driving experience. Participants were informed that they were free to withdraw at any time if they felt uncomfortable with the experiment. After the preparation, the participants performed the assigned tasks and subsequently filled out a set of questionnaires, which was the evaluation on the perceived complexity. Half of the participants performed infotainment tasks first, and the other half performed air conditioning-related tasks first. Figure 1 shows the experimental environment. The order of the experiment vehicles was randomized to eliminate the possibility of learning effects and fatigue. Finally, a quick interview regarding the in-vehicle controllers was conducted. The total time taken for the procedure was approximately 90 min. Figure 2 shows the overall procedure of the experiment. The experimental procedure was approved by the Yonsei University Institutional Review Board.

3.4. Data gathering

Interface design variables

We limited the scope of the study to the controllers in the steering wheel and the center fascia of the vehicle. Interface design variables, which are listed in Table 1, were measured for developing a complexity model. Three different researchers evaluated the interface design variables for each vehicle. We first created a guideline to standardize the measurement process. Based on the guideline, the three researchers independently measured data for the variables in all the vehicles to reduce the possibility of errors. After measuring the variables individually, we compared the three sets of data to determine the values. Table 2 presents the calculated minimum, maximum, and mean values of the measurement variables obtained from 10 vehicles.

Subjective complexity assessment

We collected subjective complexity assessment data from the participants to develop a statistical model of controller complexity. A questionnaire was used to evaluate complexity, and questionnaire items were developed based on previous studies (Ling et al., 2013; Xing, 2008). The questionnaire was developed to evaluate three items of controller complexity and one item of satisfaction. The items for evaluating complexity were as follows: (1) overall, controllers of the vehicle are too complex to perform the task, (2) the controllers of the vehicle are difficult to use, and (3) the control interface of the vehicle is simply designed. Every item was written in Korean as all participants were Koreans. We checked the conformity of each item regardless of whether items were written in English or Korean. The responses were recorded on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree), and one reverse-scored item was used to detect untruthful responses. We verified the reliability of the questionnaire items using Cronbach’s alpha coefficient ($\alpha = 0.880$). In addition, we conducted a quick interview before ending the experiment that included questions about the difficulty of the tasks.

Task performance

We used cameras to record the experimental procedure to verify the task performance. We calculated the task performance based on video images. First, we classified task success using the following criteria: If a participant took more than 15 s to perform a task, the task was considered a failure based on the 15s rule for driver information systems derived from a previous study (Green, 1999). In addition, if the objective of the task was not achieved, even though the participant

![Figure 2. Overall procedure of experiment.](Image)
conducted the task within 15 s, the task was also classified as a failure. All the tasks were classified as either success or failure. Based on the results, we calculated the success rate for each vehicle with each participant.

4. Results

4.1. Results of subjective controller complexity evaluation

All statistical analyses in the present study were performed using IBM SPSS Statistics version 22.0. The average score of controller complexity of each vehicle ranged from 2.4 to 4.57. One-way analysis on variance (ANOVA) of the vehicle variables showed that the participants evaluated complexity levels differently (F = 60.45, and p < 0.01).

Based on the average score of controller complexity, we divided the vehicles into two groups: high and low. The average score of the high complexity group was 4.06, and the average score of the low complexity group was 2.52. The results of one-way ANOVA showed that significant differences existed between the two groups (F = 394.79, and p < 0.01).

4.2. Regression model for assessing controller complexity

We verified the basic assumptions for regression analysis. We included all measurement variables for building a model, as the correlation analysis showed that every variable is significantly correlated to the perceived complexity. We used the multiple linear regression method to build the statistical model.

Table 3 provides the overall results of the regression analysis. The developed model was statistically significant (F = 57.04, p < 0.01) and explained approximately 37% of the variance in complexity levels. The Durbin–Watson value was 1.940, which is close to 2, indicating that there was no autocorrelation problem. The variance inflation factor (VIF) values of all the variables of the model were below 10, meaning that there was no multicollinearity problem.

Results showed that two variables in the functional dimension are significant predictors of perceived controller complexity (β = 0.092, p < 0.01; β = 0.112, p < 0.01). Behavioral dimension variables were excluded from the model because of high correlation with other variables. In the structural dimension, variables showed different relationships depending on their characteristics. Three variables, namely the distance from the steering wheel edge to the steering wheel controller, the number of indicator lamps, and the size of the controller, showed a negative correlation with the complexity level (β = −0.212, p < 0.01; β = −0.207, p < 0.01; β = −0.493, p < 0.01); two variables represented a positive correlation; however; one variable was not statistically significant (β = 0.025, p = 0.829; β = 0.482, p < 0.01). The other three variables in the structural dimension, namely the number of controller groups, ratio of controllers in group, and overlapped controllers, were excluded from the model.

4.3. Control task performance results

An experiment was designed to examine the effect of controller complexity on control task performance. We used the task success rate as a task performance measure. The average task success rate was relatively high, as the tasks consisted of general functions that all vehicles provide. Nevertheless, the one-way ANOVA showed that there were significant differences in task success rate between vehicles (F = 17.73, p < 0.01). To scrutinize these differences, the effects of age, gender, and the complexity level group on the task success rate were analyzed using three-way ANOVA (Table 4). We confirmed that the effect of age and complexity level group was significant, but that of gender was not. The average success rate was 0.89 for men and 0.86 for women. The average success rate according to age was as follows: 0.94 for participants in their 20s, 0.92 for participants in their 30s, 0.87 for participants in their 40s, 0.79 for participants in their 50s, and 0.75 for participants in their 60s. The average success rate was 0.82 for the high complexity level group, and 0.92 for the low complexity group. Interaction effects between each pair of variables were significant, but those between three variables were not. Figure 3 shows the differences in task performance.
4.4. Relationship between controller complexity and task success rate

To verify the validity and reliability of the developed model, we conducted several analyses. First, a correlation analysis was conducted between the aggregated scores of perceived controller complexity for each vehicle obtained from participants and the complexity model score. Results showed that these two values are highly correlated ($r = 0.91, p < 0.01$), meaning the developed model is effective for evaluating the complexity scores of controller interfaces.

In addition, we analyzed the relationship between the controller complexity scores and control task performance. Participants were required to perform 12 control tasks using in-vehicle controllers, as mentioned earlier, and the average task success rate was over 75% across all age groups. Although the task success rate was relatively high, participants felt that the controller complexity was different for each vehicle. This fact was confirmed by a correlation analysis between the complexity model scores and task success rate ($r = -0.369, p < 0.01$). There was a negative correlation between complexity model scores and satisfaction ($r = -0.646, p < 0.01$). Figure 4 shows the results of correlation analysis.

5. Discussion

In this study, we structured controller complexity and elicited measurement variables based on the FBS framework and developed a model for evaluating controller complexity based on these measurement variables. The results of the experiments showed that controller complexity levels ranged from 2.4 to 4.57, and task performances were impaired with increasing controller complexity. This indicates that the complexity concept is useful for interface evaluations, particularly as there is no appropriate guideline for evaluating in-vehicle controller interfaces even where the evaluated interfaces share a common purpose.

In the developed model, the two variables, that is, the number of single task controllers and the number of multitask controllers, related to functional complexity showed a positive correlation. An increase in the number of in-vehicle functions led to an increase in the number of controllers and the role of each controller. Results showed that increasing functional complexity factors led participants to perceive the in-vehicle controllers as being more complicated. These results are in line with the findings of previous studies, which postulated that increasing the functional complexity of a user interface results in greater perceived difficulty or deterioration of task performance. Liu and Li (2012) reviewed a number of complexity studies and concluded that the level of complexity increases with an increase in functional measures, that is, the number of goals. In addition, a technical report revealed that at least 20% of drivers that owned new vehicles had never used many of the functions in their cars (Power, 2015), as new vehicle owners replied that they did not want the functions that the vehicles provided. Specifically, drivers focused not on the benefits from...
the new functions but on negative user experiences related to increasing complexity.

We predicted that two variables in the behavioral dimension would also significantly influence perceived controller complexity. However, these variables were excluded from the developed model as they were statistically correlated with other variables. According to Khoshgofaar and Munson (1990), most design components of physical interfaces are inevitably interrelated. Thus, the results of this study also showed that some variables are correlated, although we identified that they are useful for evaluating controller complexity by reviewing previous studies.

In the structural dimension, one variable was found to have a positive correlation with complexity, while the other three variables were negatively associated with complexity. The number of dummy controllers also had a positive correlation with complexity levels. We determined that this relationship results from the fact that while dummy controllers provide aesthetic symmetry, drivers mistake them for actual buttons. On the other hand, the number of indicator lamps had a negative correlation with complexity levels. Many studies on human factors have shown that visual feedback helps users perform tasks and decreases their mental workload (Vitense, Jacko, & Emery, 2003; Zhang, Fernando, Xiao, & Travis, 2006). Therefore, it is reasonable to assume that increasing the number of indicator lamps leads to increasing complexity levels as indicator lamps play a role in providing visual feedback. In addition, the size of the controllers had a negative correlation with complexity. Results of previous studies showed that users prefer larger controllers (Kim, Kwon, Heo, Lee, & Chung, 2014).

To confirm the validity and reliability of the developed model, several analyses were performed. First, we checked the performance of the model using $R^2$. The explanation power of the model was approximately 37%, which is high enough to predict complexity levels, considering that we developed the model based on interface design variables. Second, we checked that a negative correlation exists between complexity levels and task performance. This result is in line with previous studies, which showed that human operators have difficulty performing tasks when the level of complexity is high (Lee et al., 2016; Yoon et al., 2015a).

The relationship between satisfaction and perceived complexity was also analyzed. Researchers examined these issues and obtained two types of results. Many studies found that people prefer a moderate level of complexity (Geissler, Zinkhan, & Watson, 2006; Michailidou, Harper, & Bechhofer, 2008; Reinecke et al., 2013). Reinecke et al. (Reinecke et al., 2013) explained that the domain characteristics are important. For a static task environment, such as web surfing, people prefer a balanced level of complexity because it is visually attractive and enhances trust, credibility, and impression (De Angeli, Sutcliffe, & Hartmann, 2006; Hassenzahl & Monk, 2010; Robins & Holmes, 2008). However, these preferences were different in dynamic environments such as vehicles, as the efficacy of tasks is more important than aesthetics in these environments. In other words, users want to perform the task effectively, and it therefore is preferred that an interface has a low level of complexity.

In addition, we obtained several insights from the data obtained from quick interviews. Some participants pointed out that finding the controllers for several tasks was difficult. This issue resulted from difficulties in understanding the meaning of icons or terms. In case of the AM/FM mode change task, most participants succeeded at the task if “AM/FM” was written on the controllers. However, the controllers in several vehicles utilized terms such as “RADIO,” “BAND,” or “MODE.” In these cases, it was more difficult for participants to recognize these controllers for the task. Additionally, some participants had trouble controlling the temperature because they did not understand the term “TEMP.” One participant reported problems in understanding terms as follows: “Sometimes, the term on the button is hard to understand. Who has ever used a term like ‘BAND’... ‘SETUP’ button has different functions that differ from vehicle to vehicle.”

In addition, several participants could not find status changes on the information display. Specifically, these errors occurred when participants performed air conditioning tasks. Several vehicles used the “MODE” controller to change air direction. If participants push the controller, air conditioning modes can be changed to three or four alternatives, and the status is presented on the display. However, some participants could not find the controls for changing the air direction on the interface and they gave up on completing the task. We received the following comment relating to this failure: “I think one button should directly relate to one function. For example, selection of air direction mode with ‘MODE’ button, it is hard to see the display without attention.”

Some issues were found because of the inconsistency between the mental models of the participants and the mechanism of the controllers. For example, in the case of the button presented in Figure 5(a), drivers can change air conditioning modes using the red indicator on the outside button. However, many participants tried to change air conditioning modes using the inner and smaller inner buttons. The participants showed similar behaviors when they performed the task using the buttons shown in Figure 5(b) and 5(c). The controller in Figure 5(b) is used for three functions: to
In the case of a task based on the nominal controller, it provides drivers with difficulties in performing tasks, such as searching for target controller. Additionally, the number of single task controllers and multitask controllers are related to the functional complexity provided by the system, thus increasing the perceived complexity of in-vehicle controllers. The multitask controller has the advantage of integrating several single task controllers, but it requires a trade-off because more cognitive processes are needed to perform the tasks compared to using a single task controller.

The characteristics of controllers change depending on the tasks, because there is a difference in required behaviors depending on the task type and characteristics. In the case of a task based on the nominal controller, it is necessary for the driver to accurately confirm the desired state (e.g., change and check the direction of wind). Whereas in the case of the task based on continuous interval controller (e.g., increase/decrease volume), it is not required for drivers to check the particular state of results. In this study, the behavioral dimension is excluded from the statistical model due to the correlation between the attribute of the physical controllers. However, considering the importance of the behavioral characteristics of task, this dimension needs to be considered for designing controller complexity.

The physical interface variables included in the structural dimension have a different effect depending on the characteristics of each variable. Dealing with the trade-off effects between visual complexity and cognitive complexity is important. Grouping and simplification within a physical interface can bring benefits regarding both visual and aesthetic aspects, but it is likely to cause cognitive difficulties in the actual task process.

### Table 5. FBS complexity dimensions-related issues.

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Issues</th>
</tr>
</thead>
<tbody>
<tr>
<td>Functional</td>
<td>- The functional complexity of the in-vehicle systems provides drivers with difficulties in performing tasks, such as searching for target controller.</td>
</tr>
<tr>
<td>Structural</td>
<td>- The physical interface variables included in the structural dimension have a different effect depending on the characteristics of each variable.</td>
</tr>
<tr>
<td>Behavioral</td>
<td>- The characteristics of controllers change depending on the tasks, because there is a difference in required behaviors depending on the task type and characteristics.</td>
</tr>
</tbody>
</table>

Based on findings of the study, we summarized the issues that were related to each complexity dimension and variables (Table 5).

## 6. Conclusion

This study focused on evaluating in-vehicle interfaces using the theoretical concept of complexity and provided several academic and practical implications. First, the study extends on existing complexity studies pertaining to human–computer interactions and human factor fields. Although researchers have focused on complexity studies for many years, research domains are limited (e.g., visual complexity and task complexity). Therefore, our study could allow researchers to study complexity in greater depth. Second, we selected contributory factors to complexity based on the FBS framework and tested the influence of these variables on controller complexity. Using this process, we verified the applicability of the existing knowledge and the FBS framework for use in interface development and design theory. Finally, we investigated difficulties when drivers use the in-vehicle control interface based on the results of the developed model and quick interview.

Several issues should be considered in future studies. Several variables were excluded from the developed model because of their correlations. Although these variables did not statistically explain controller complexity, it does not mean that they are unimportant. Accordingly, further studies should be conducted to verify the effects of these variables. In addition, participants evaluated in-vehicle controllers under the assumption that only physical controllers are used. Although it is important to evaluate interfaces for traditional interactions, the current trend is to adapt various interactions with vehicle systems. Thus, future studies should analyze the complexity of new interfaces for other interactions, including touch interactions, gesture interactions, and voice interactions.

## Acknowledgments

This research was supported by the Graduate School of YONSEI University Research Scholarship Grants in 2017.

## Funding

This work was also supported by Mid-career Researcher Program through NRF grant funded by the MSIP (Ministry of Science, ICT and Future Planning) (Grant # NRF-2013R1A2A2A0301450).

## ORCID

Yong Gu Ji http://orcid.org/0000-0002-0697-2164

## References


dialling task. *Ergonomics*, 42(8), 1015–1037. doi:10.1080/001401399185117


About the Authors

Seul Chan Lee is a Ph.D. candidate in the Department of Industrial Engineering at Yonsei University, Korea. His research interests include HCI and human factors issues in vehicle environments and smart devices. seulchan@yonsei.ac.kr

Yong Gu Ji is a Professor in the Department of Industrial Engineering at Yonsei University, where he directs the Interaction Design Laboratory. He received his Ph.D. in Human Factors/HCI from Purdue University. His research interests include usability/UX in smart devices and self-driving vehicles.