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Research Article

Evaluation of Preferred Automated Driving Patterns Based on a Driving Propensity Using Fuzzy Inference System

Sooncheon Hwang [1] and Dongmin Lee [2]

[1]*Department of Smart City, University of Seoul, 163 Seoulsiripdae-ro, Dongdaemun-gu, Seoul 02504, Republic of Korea*
[2]*Department of Transportation Engineering & Department of Smart City, University of Seoul, 163 Seoulsiripdae-ro, Dongdaemun-gu, Seoul 02504, Republic of Korea*

Correspondence should be addressed to Dongmin Lee; dmlee@uos.ac.kr

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With the rapid advancements in automated driving technologies, there is a growing demand for the commercialization of advanced automated vehicles. Through these technologies, we envision enjoying various types of entertainment in automated vehicles, apart from manual driving. To achieve widespread acceptance of automated driving, appropriated interactions between users and automated driving systems must occur. From users' perspective, automated driving vehicle must be operated within users' comfort, safe, and satisfying perception based on their personal driving style such as aggressive and defensive driving. Thus, during the motion planning phase of automated driving, consideration should be given to the implementation of a behavioral algorithm based on user propensity. However, user preferences for automated driving patterns exhibit considerable variation, making it essential to conduct an in-depth investigation into the preferred automated driving patterns corresponding to users' propensity. In this study, we confirmed that the characteristics of preferred automated driving patterns can be deduced from comprehensive driving propensities, which were derived by combining inherent driving propensities with simulator-based driving behavior characteristics using the fuzzy logic method. This study confirmed that in the era of automated driving, the preferred automated driving patterns may vary depending on the propensity from the user's perspective. Considering these differences, it is meaningful in which it suggests the need for automated driving motions to be implemented based on individual preferences that appear according to human factors such as user propensity.

1. Introduction

With the continuous rapid development of automated driving technologies, the transformative changes that it will bring to people's daily lives are being increasingly anticipated [1]. People eagerly anticipate freedom of driving, enabling them to engage in other activities while commuting. Although these expectations may seem feasible, it is challenging to assert that there will be no inconvenience in using automated driving vehicles, considering the uncertainty surrounding actual driving behaviors. Expectations for automated driving vehicles are not only that accidents do not occur on the road but also that automated driving is implemented that users can trust while driving naturally in traffic flows. Building trust in automated driving systems requires accommodating individual driving propensities because automated vehicle users might evaluate automated driving systems based on their driving experience and propensities whether too fast or too slow. The realization of the expected era of automated driving hinges on establishing a high level of trust in these systems.

On the contrary, the wider the gap between people's expectations of automated driving and its reality, the greater the potential for anxiety and stress in users. In severe cases, physical discomfort such as motion sickness can reduce the acceptance of automated driving vehicles [2]. Therefore, it is essential to shift the focus of human factors research from drivers' perspectives to those of automated vehicle users [3].

Instead of solely investigating the cognitive reactions related to driving behaviors, how individual preferences and acceptance manifest in various automated driving situations must be explored. Moreover, different human drivers have different driving styles, expectations, and preferences. Those differences make different perspectives, satisfaction, and stress regarding automated driving.

Previous studies have demonstrated a distinction between individuals' inherent driving propensities as drivers and their preferred driving behaviors as passengers [4–6]. The inherent driving propensity refers to the subjective assessment of an individual's psychological characteristics, particularly their self-evaluated driving skills and habits. They showed that the acceptance of automated driving can be significantly enhanced by tailoring the driving behavior of automated vehicles to align with the users' individual preferences in level 4 or higher automated driving environments. Users desire automated driving experiences that align with their preferred driving styles, considering specific roads and driving conditions. It is crucial to establish a connection between the preferred automated driving patterns of individuals with varying propensities, as this will guide the development of highly desirable and well-accepted automated driving technologies.

Driving propensities refer to temperament or approach that favors psychological decisions and behaviors based on the driver's attitude and judgment in actual traffic situations [7]. Numerous studies have investigated the relationship between specific driving behaviors, including individual driver propensity and engagement in aggressive or dangerous driving behaviors [7–12]. In these studies, propensities were defined by assessing individual personality traits or categorizing driving behaviors recognized by individuals, such as their typical driving habits. Consequently, a methodology was developed to objectively categorize driving behaviors that are subjectively recognized by each person by employing well-designed questionnaires and evaluating them based on consistent criteria. Prominent examples include the Driving Behavior Questionnaire (DBQ) developed by Reason et al. [13] and the Driving Anger Scale (DAS) developed by Deffenbacher et al. [14].

The original DBQ comprises five measures for assessing dangerous or safe driving behaviors: slips, lapses, mistakes, unintended violations, and intentional violations. Since its inception, the DBQ has been applied and refined in various studies, establishing itself as a prominent approach for evaluating dangerous or safe driving behaviors [15–20]. The DAS consists of six measures assessing hostile gestures, illegal driving, police encounters, slow driving, rude driving, and traffic obstruction. Other researchers have modified the scale and questions of the DAS to align with specific research purposes and investigation settings [21–23]. These survey-based methods for evaluating driving propensities have been extensively employed in various studies as indirect measures of driving ability. Nevertheless, it is challenging to directly apply the survey results because of the relative nature of the derived driving propensities. As the driving propensities obtained from these surveys are mostly used for relative evaluation, it is necessary to present comprehensive methods for evaluating driving propensities in combination with other variables, particularly when working with limited sample sizes.

Driving behaviors refer to the intentional or unintentional characteristics and actions that manifest during the driving process, influenced by various factors such as an age, experience, gender, attitude, and emotions [24–27]. These internal and external factors are known to affect risk assessment in various road traffic situations, leading to changes in driving behaviors such as driving speed, acceleration, deceleration, and steering, depending on the circumstances. Generally, driving behaviors are characterized on a spectrum ranging from defensive to risky and aggressive actions and can be estimated based on the characteristics of driving behaviors.

A method based on the level of individual perception has the advantage of indirectly deriving driving propensities for several people using a simple method. However, it has limitations in directly relating to the actual driving behavior. Therefore, deriving characteristics from the observed driving behaviors can serve as an objective factor for evaluating driving propensities. Previous studies have employed driving speed, overtaking behavior, intervehicle distance gap, and deceleration and acceleration as factors for evaluating driving propensities [28, 29]. Although evaluating driving behaviors under real-world road conditions is ideal, practical limitations exist owing to safety concerns and restricted experimental conditions. Consequently, driving simulators have been employed to evaluate driving behaviors [30–33]. Related studies have derived and utilized variables such as driving speed, deceleration and acceleration, lateral placement, intervehicle distance gap, and time-to-collision (TTC), which are manifested based on driving situations to define driving behaviors. These variables represent behavioral patterns that differ according to individual driving preferences, thereby serving as suitable indicators for defining driving behaviors. Furthermore, a study substantiated the appropriateness of using a driving simulator to derive driving behaviors through a comparative analysis of simulator-derived and actual vehicle driving data [33].

Fuzzy theory can cluster by synthesizing the characteristics of variables related to driving propensities. It is a theoretical framework that acknowledges the ambiguity of subjective evaluations and quantifies the degree of ambiguity when deriving objective inference results [34]. Typically, the inference process using fuzzy theory involves three steps: fuzzification, fuzzy inference, and defuzzification. Fuzzy logic has been applied in various studies by transportation engineers, including surveys on the interaction between drivers and road facilities [35, 36], investigations of interactions between drivers and in-vehicle systems [37, 38], and psychological personality tests of drivers [39]. It has been widely utilized particularly in research endeavors aimed at defining driving styles using fuzzy logic.

A representative example is the study conducted by ububranicé-Dobrodolac et al. [40], in which four different surveys were integrated using fuzzy logic to derive driving propensities that contribute to traffic accidents. This study employed a fuzzy inference system (FIS) that was used to infer the propensities based on the results of four surveys to assess individual propensities, and the number of traffic accidents was used to validate the results from the FIS. Interestingly, the results obtained using the FIS outperformed those of the regression model, suggesting that the FIS may be suitable for synthesizing and categorizing subjective human evaluations. In addition, studies have utilized driving data, such as driving speed, acceleration, and intervehicle distance gap, to define driving styles using fuzzy methods [41–43]. This approach has the advantage of deriving relatively accurate driving behaviors by analyzing actual driving data acquired from drivers. However, challenges arise in obtaining real-world driving data, and it is difficult to collect all required data within the same road traffic environment. Consequently, more comprehensive results can be obtained by combining survey-based propensity evaluations with driving behavior measurements to accurately specify driving propensities.

In recent years, extensive research has been conducted to determine the preferred automated driving styles from the user's perspective [4–6, 44]. The reason behind these user evaluations by defining the automated driving style is that the comfort felt when boarding a vehicle is mainly influenced by the driver's driving style [24–26], so the driving patterns can be judged according to the style in which the vehicle is driven even when boarding the automated vehicle. Factors that distinguish driving style include changes in driving speed according to acceleration, deceleration, and movement in the vertical direction. Driving styles can be defined in three main concepts, and these concepts are used similarly to define autonomous driving styles: aggressive or dynamic, casual or modulate, and comfortable or defensive. Existing studies have primarily focused on identifying the universally preferred automated driving patterns among users. However, little research has been conducted on deriving the preferred automated driving patterns based on individual propensity.

Individuals who favor aggressive driving may experience frustration and nervousness when exposed to defensive driving. Conversely, in other cases, some individuals may experience anxiety and discomfort in response to aggressive driving. Given these considerations, identifying the common propensities that influence the preferred automated driving patterns from the user's perspective could potentially resolve negative evaluations of automated driving. To achieve this, this study aimed to derive the driving propensities that influence preferences for automated driving patterns. This was accomplished by utilizing fuzzy logic to derive comprehensive driving propensities based on the evaluation of survey-based inherent perceptions and simulator-based driving behaviors. In addition, this study evaluated the preferences for automated driving patterns implemented in five modes to investigate any common characteristics in preferences based on propensity.

2. Methodology

In this study, an evaluation of preferred automated driving patterns based on driving propensities was conducted through four steps: surveys to evaluate driving propensities, investigation of driving behavior characteristics, development of FIS to evaluate comprehensive driving propensities, and assessment of preferred automated driving patterns. Driving propensities were evaluated using two surveys. The first survey was conducted using simple questionnaire that the participants directly selected their perceived driving propensity, and the second surveys were conducted based on the DBQ and DAS method. Driving behaviors were investigated for using input variables of driving behavior characteristics to derive comprehensive driving propensities through FIS. In addition, those were used to decide parameter values of automated driving patterns using VR driving simulator experiments. Then, the FIS to evaluate comprehensive driving propensities was developed using the results from second surveys and driving simulator experiments. Finally, preferred automated driving patterns were evaluated through investigating preference order regarding automated driving scenarios implemented based on the parameters of driving behaviors.

For the survey and experiments, a total of 36 individuals participated as follows: 11 participants in their 20s, 11 in their 30s, 7 in their 40s, and 7 in their 50s (Table 1). Out of all the participants, 27 were male and 9 were female. All of them held valid driver licenses and were recruited based on their driving frequency of at least once a week. Before the experiment, they were informed about the possibility of experiencing motion sickness during the simulator experiments and the data collection of their driving behaviors. The experiments proceeded only after obtaining the participants' agreement.

2.1. Surveys for Driving Propensities. In this study, the driving propensities of the participants were assessed by two survey methods. First, the participants directly selected their perceived driving propensity in their daily life using simple questionnaire. The participants were asked to choose the most accurate item among the following four categories when questioned about what they perceive their driving propensity to be: Defensive, Less Defensive, Less Aggressive, and Aggressive. The choice of these four categories was intended to provide a clearer classification of the participants' driving propensities by avoiding the possibility of choosing options in the middle like neither defensive nor aggressive that people easily answer without sufficient consideration. The responses were used to compare the comprehensive driving propensities based on the fuzzy method.

The second survey method used DBQ and DAS designed to derive inherent driving propensities. The DBQ was employed to determine the inherent safe driving propensities. The DBQ, which was improved according to the situation in Korea [20], consists of six subcategories for evaluating safe driving behaviors: driving errors, cautious driving, violation, considerate driving, self-regulation, and aggressive driving. The questionnaire comprised a total of 39 questions, and participants rated their responses on a five-point scale, ranging from "never" (1 point) to "almost always" (5 points).

Table 1: A configuration of the participants.

Age	Gender		Total
	Male	Female	
20s	9	2	11
30s	8	3	11
40s	5	2	7
50s	5	2	7
Total	27	9	36

Next, the inherent reckless driving propensity was derived using the DAS survey. In this study, a modified version of the survey questions and structure tailored to the Korean context was utilized [19]. The modified DAS consisted of five categories of measures: discourtesy, hostile gestures, slow driving, traffic obstruction, and illegal driving. A total of 21 questions in the questionnaire items were used to assess the level of anger experienced by the participants for each question, ranging from "not angry at all" (1 point) to very angry" (5 points).

The propensity index was then calculated by averaging the scores for each characteristic. A higher score indicated a greater inclination towards safe or reckless driving propensities. The obtained scores were then utilized to classify the inherent driving propensities into four groups using the FIS.

2.2. Experiments Using a VR Simulator. In this study, the driving simulator experiments to analyze individual driving behavior characteristics of participants and to evaluate preferences for automated driving patterns were conducted separately. The experiment was first conducted to analyze the individual driving behavior characteristics of the participants. The driving behavior characteristic data derived through the experiment were used as input variables for FIS to derive the comprehensive driving propensities. In addition, parameter values were calculated based on the driving behavior characteristic data and used to implement automated driving patterns for each type as VR simulators.

In the second driving simulator experiment, the same participants evaluated their preferences for five automated driving patterns implemented in VR simulations. The two simulator experiments were conducted in virtual identical road environments. To exclude any familiarity that participants might have with the same road environments, the two experiments were conducted with a gap of three weeks between them.

2.2.1. Apparatus. The driving simulator utilized in this study was designed to enhance screen immersion by incorporating a semi-dome-shaped screen installed at the VR Center at the University of Seoul. The equipment, as depicted in Figure 1, provides an environment that allows participants to immerse themselves in a driving scenario to the maximum extent possible. This was achieved by implementing a driver seat that replicates the characteristics of an actual vehicle and using a screen that surrounds the driver seat. Such a setup ensures an appropriate performance and environment for evaluating satisfaction based on the subject's movements, as they are fully immersed in the implemented automated driving patterns.

2.2.2. Experiment Scenario Design. To evaluate the participants' driving behaviors and preferred automated driving patterns in the VR simulator experiments, a 6.6 km long urban expressway with three lanes and an 80 km/h speed limit in Seoul was designed. Figure 2 shows that the simulated road was subdivided to match various traffic environments, allowing for a detailed analysis of the participants' driving behaviors and a more refined emulation of automated driving pattern characteristics. As shown in Table 2, Section 1 simulates the driving conditions of Level of Service (LOS) C in traffic flow. This section was designed to evaluate participants' regular driving habits in typical traffic flow, such as following and overtaking. Subsequently, Section 2 replicates the LOS F traffic conditions, enabling the measurement of driving behaviors in congested traffic flow situations. Section 3 is implemented after the congestion scenario, which represents slow-moving conditions, to analyze driving behavior in frustrating driving situations. The scenario ends with a slow driving of approximately 0.6 km until reaching the exit and subsequently exiting the highway via the ramp.

2.2.3. Experiments Procedure. The driving simulator experiment to derive the characteristics of the participants' driving behavior was conducted in the following way. Prior to the experiment, a preliminary "warming driving" was conducted to ensure that the participants were familiar with driving using a driving simulator and to exclude participants who experienced any motion sickness or discomfort in the conditions of driving using a VR simulator. The "warming driving" was repeated until the participants felt that they could drive like their usual driving habits. After the completion of "warming driving," this experiment was conducted after confirming that the participants were ready. The participants were instructed to commence driving on the urban expressway and drive towards a predefined destination, i.e., Bongeunsa Temple. The driving experiment was conducted only once.

2.3. Investigation of Driving Behaviors. Among the various driving behavior variables derived from the driving simulator experiment, driving speed, acceleration/deceleration, and intervehicle distance gap were used as indicators to

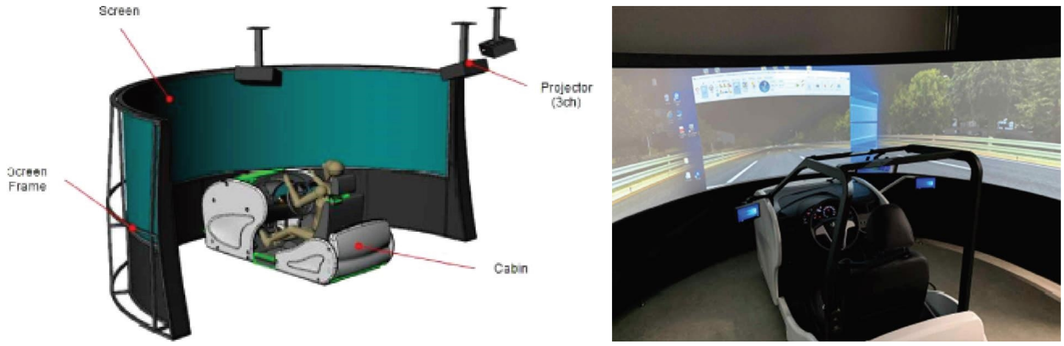

Figure 1: Driving simulator equipment utilized in the study.

(Section 1) (Section 2) (Section 3) (Section 4)

Figure 2: Implementation of road traffic environments by sections.

Table 2: Design characteristics of road sections.

Sections	Length of roads (km)	LOS	Event items and studying situations	Specifications of other vehicles
1	3.8	LOS C	Driving for car-following and overtaking	Speed: 70 to 85 kph Headway: 60 to 160 m
2	0.8	LOS F	Driving in congested situations	Speed: 10 to 20 kph
3	1.4	LOS D	Driving in slow-moving situations	Speed: 50 to 70 kph
4	0.6	—	Driving on a ramp	—

confirm driving behavior characteristics. It was confirmed that those were used as major indicators for evaluating driving behaviors in the existing literature [4–7]. The data were derived from the driving log data recorded when the simulation program was running. The driving log data are recorded at intervals of approximately 0.1 seconds. To derive driving behavior characteristics, preprocessing was first performed on data for each major indicator at 1 m intervals based on the driving distance. Among the data organized in this way, the driving speed used the data value itself recorded on the log data. In the case of deceleration and acceleration, the speed (m/s), time (second), and distance (m) values among the data processed in units of 1 m were used to derive each section. The intervehicle distance gap was derived through the difference in vehicle position (m) according to the movements between the participants' driving vehicle and the front vehicle.

The derived driving behavior characteristics were utilized as lower-level input variables in analyzing comprehensive driving propensities through FIS. The classification of driving propensity types based on driving behavior characteristics was carried out using the following method: the aggressive driving propensity was identified in accordance with relatively higher driving speed, faster acceleration, and shorter intervehicle distance gap, whereas defensive driving propensity was observed in cases of relatively lower driving speed, slower acceleration, and longer intervehicle distance gap. The four groups of driving behavior propensities were derived using the FIS based on driving behavior data.

2.4. Development of the Fuzzy Inference System to Evaluate Comprehensive Driving Propensity. This study employed a fuzzy inference model to comprehensively analyze and categorize the driving propensities for each participant. The inference process based on the fuzzy method involves several stages, namely, fuzzification, fuzzy inference, and defuzzification. To facilitate the fuzzification process, a trapezoidal membership function that effectively expresses the linguistic scale of statements was utilized. This function is characterized by four parameters, and its affiliation is determined according to the following formula:

$$\text{trapezoid}\, f(x,a,b,c,d) = \begin{bmatrix} 0 & x \le a \\ \dfrac{x-a}{b-a} & a \le x \le b \\ 1 & b \le x \le c \\ \dfrac{d-x}{d-c} & c \le x \le d \\ 0 & d \le x \end{bmatrix}. \quad (1)$$

The FIS was constructed based on the trapezoid membership function, following the steps outlined below. First, based on the survey results concerning safe driving and reckless driving propensities, the FIS lower level was designed to derive the inherent driving propensities. The membership function used to infer the inherent driving propensities employed the centroid values of each cluster, derived through k-means clustering analysis. The k-means clustering is an analytical method where given data characteristics are clustered into k groups with similar attributes. In this method, data are randomly chosen and assigned to clusters based on their proximity to the centroid. Iteratively, clustering is performed, and optimal centroid values are determined. The centroid values determined here are utilized as parameter values to distinguish driving propensity types. In this study, the derived DBQ and DAS scores of all participants were analyzed into three clusters, and the centroid value formed for each cluster was used as the membership function.

The inherent driving propensities were then categorized into four groups, DP 1 to DP4, by synthesizing the fuzzy index of safe driving and reckless driving propensities, which were classified according to the set of the membership functions. Cases exhibiting a relatively high inclination towards safe driving propensity or a relatively low inclination towards reckless driving propensity were assigned to DP 1. DP 2 comprised cases with high safe driving propensity and normal level of reckless driving propensity. DP 3 denoted cases with normal level of safe and reckless driving propensities, whereas DP 4 represented cases displaying both low safe driving propensity and high reckless driving propensity.

Subsequently, four distinct groups were derived from the driving behavior characteristics obtained through the first driving simulator experiments. To explain the driving behavior characteristics, longitudinal and lateral acceleration, driving speed, intervehicle distance gap, longitudinal deceleration, and driving speed on a ramp were selected as explanatory input variables for FIS. The variables of speed and distance gap used to analyze the driving behaviors reviewed in previous studies [45–48] and those of driving speed, acceleration, and deceleration recognized by the participants during this experiment were important in defining the driving behavior characteristics.

The membership functions for the six input variables in the FIS were defined as follows: for the deceleration and acceleration, reference values from existing studies [45–48] and the dangerous driving behavior index provided by the Korea Transportation Safety Corporation [49] were utilized. The acceleration values in general driving situations were set to 0.9 and 1.5 m/s^2, whereas the acceleration values in lateral driving situations were set to 0.9 and 3.0 m/s^2. The deceleration values in the designated situations were set to 2.0 and 3.0 m/s^2. The membership functions were defined as low, medium, or high to represent different levels of driving behaviors. For driving speeds, the membership function was determined based on the speed limits of the implemented road. For Sections 1 and 4 with speed limits of 80 and 40 km/h, respectively, the driving speed was categorized as slow or fast. Moreover, the distance gap to develop membership function was classified as short or long based on the speed limit.

In total, 216 ($3 \times 2 \times 2 \times 3 \times 3 \times 2$) rules were established to infer the defined input variables. It was inferred as the defensive driving behavior characteristic (DB 1) when maintaining low acceleration and deceleration, slow driving speed, and long-distance gap and showing more aggressive behaviors (medium-level acceleration or deceleration, fast driving speed, and short-distance gap) in up to three of the six variables. In addition, cases showing more aggressive behaviors for four to six input variables were inferred as moderate driving behavior characteristic (DB 2). Finally, cases of showing high acceleration and deceleration while generally exhibiting more aggressive behaviors were considered aggressive driving behavior characteristic (DB 4), and those showing high deceleration or acceleration only in one or two related variables were considered less aggressive driving behavior characteristic (DB 3).

The FIS model was employed to determine the comprehensive driving propensities of individuals by utilizing the fuzzy index derived from inherent driving propensities and driving behavior characteristics as input variables. By utilizing the fuzzy index inferred from the lower level, a membership function was established to classify lower index values as indicative of a more defensive driving propensity, whereas higher index values suggested a more aggressive driving propensity, as shown in Table 3. The final comprehensive driving propensities were classified into five groups: Group 1 for defensive driving propensity, Group 2 for less defensive driving propensity, Group 3 for moderate driving propensity, Group 4 for less aggressive driving propensity, and Group 5 for aggressive driving propensity. The structure of the entire FIS is shown in Figure 3. The FIS was analyzed using the MATLAB (ver. r2021a) program.

2.5. Implementation and Evaluation of Automated Driving Patterns. Second driving simulator experiment was conducted to confirm the preference tendency of automated driving patterns based on each driving propensities based on the perceived driving propensity through questionnaire and the comprehensive driving propensity derived through FIS. The automated driving for the experiment was implemented

Table 3: FIS rules for deriving comprehensive driving propensities clusters.

FIS		Driving behavior characteristics			
		DB 1	DB 2	DB 3	DB 4
Inherent driving propensities	DP 1	Group 1	Group 1	Group 2	Group 3
	DP 2	Group 1	Group 2	Group 3	Group 4
	DP 3	Group 2	Group 3	Group 4	Group 5
	DP 4	Group 3	Group 4	Group 5	Group 5

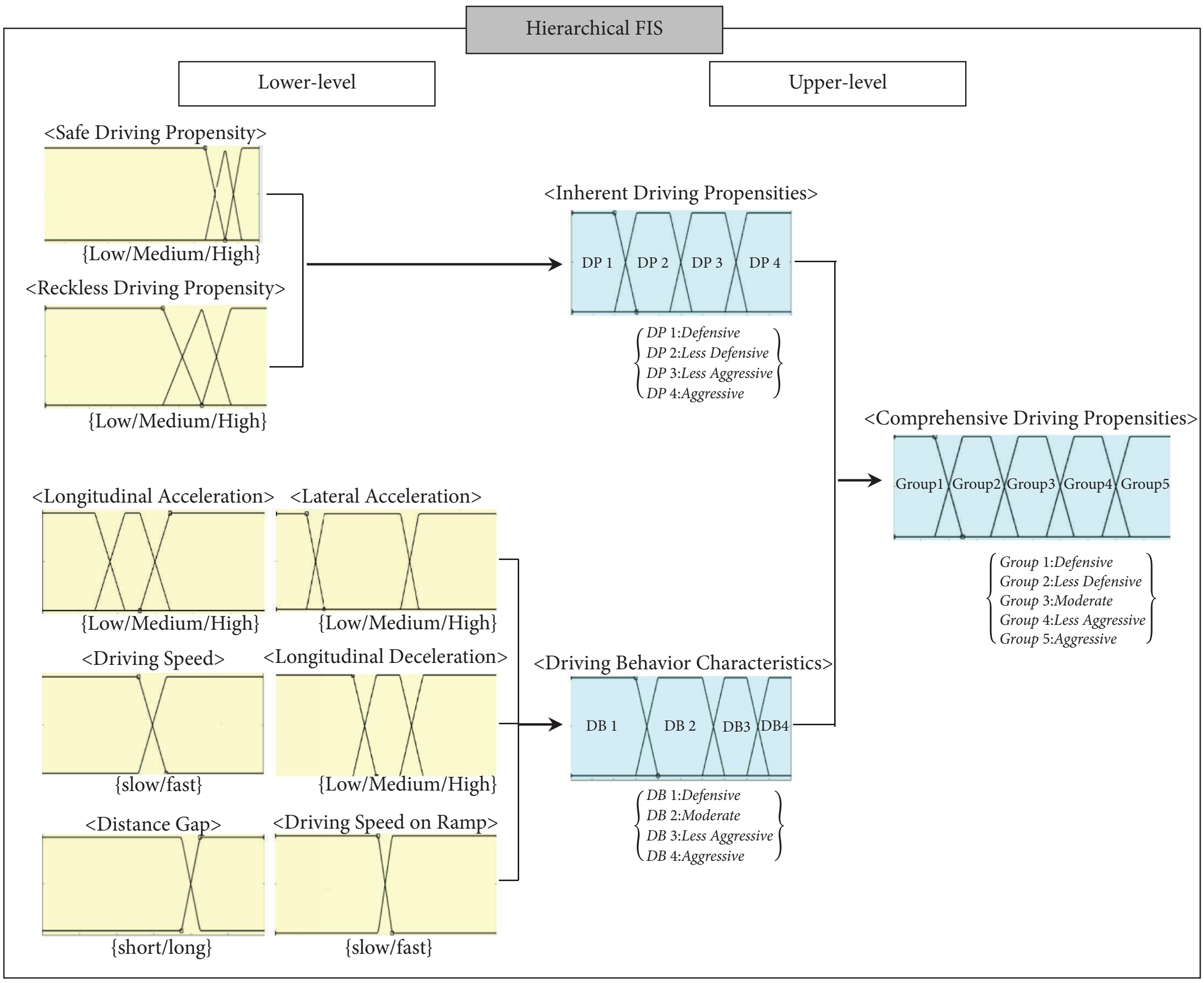

Figure 3: Hierarchy of the FIS model for deriving comprehensive driving propensities.

as a virtual environment assuming the Lv.4 level defined by the SAE [50]. To evaluate the preference for the five modes of automated driving patterns, the driving behavior characteristic data derived through the first driving simulator experiment were used to set the characteristics of each type to appear. The parameter values such as driving speed, acceleration, deceleration, and intervehicle distance gap, which determine the five modes of automated driving patterns, were defined according to the following criteria. In the distribution of driving behavior data of all participants, the minimum value, 15 percentile, average value, 85 percentile, and maximum value were used as parameter values that implement five automated driving patterns each. This approach, as utilized in Lee et al.'s [6] study, assumes that people would prefer automated driving patterns like their own driving behaviors from a user's perspective. In addition, to ensure clear differentiation between the five automated driving patterns from a user perspective, correction values were applied to set parameter differences at consistent intervals.

For instance, in the case of acceleration, the values derived from the driving experiment were as follows: minimum value 0.1, 15^{th} percentile 0.53, average value 0.99, 85^{th} percentile 1.55, and maximum value 1.84 as shown in Table 4. In the process of implementing these values as automated driving patterns, they were adjusted to have consistent differences of 0.1, 0.5, 1.0, 1.5, and 2.0, respectively. For deceleration, the derived characteristic values

Table 4: Setting values of driving characteristics based on automated driving patterns.

No.	Classification of A.D patterns	Criteria of driving behaviors	Average of acceleration (m/s^2)		Average of deceleration (m/s^2)		Average of driving speed (km/h)		Average of distance gap (m)	
			D.B	A.P	D.B	A.P	D.B	A.P	D.B	A.P
1	Defensive	Min.	0.10	0.1	−1.42	−1.5	71.36	70.00	31.36	110.00
2	Less defensive	15th percentile	0.53	0.5	−2.12	−2.2	75.65	75.00	47.09	90.00
3	Moderate	Average	0.99	1.0	−2.74	−2.8	81.52	80.00	67.66	70.00
4	Less aggressive	85th percentile	1.55	1.5	−3.3	−3.4	87.26	85.00	96.01	50.00
5	Aggressive	Max.	1.84	2.0	−3.95	−4.0	90.18	90.00	114.92	30.00

A.D: automated driving; D.B: driving behaviors observed; A.P: setting values of automated driving patterns.

were −1.42, −2.12, −2.74, −3.3, and −3.95, respectively, and similarly adjusted to be used as automated driving pattern parameter values: 1.0, 2.0, 3.0, 4.0, and 5.0. Using the same method, parameter values for other elements were set by adjusting the derived values based on predetermined criteria, ensuring consistent intervals between them.

Participants conducted driving simulator experiments to evaluate preferences for each mode of the five implemented automated driving patterns using the following method. Participants keeping their driver seat in the driving simulator evaluated their preference regarding various automated driving such as aggressive driving mode or defensive driving mode. After each automated driving pattern simulation run was completed, participants evaluated their priority preferences, including all of the previously performed simulation runs in other modes, and allowed them to modify the previously evaluated result until the final preference was determined.

3. Results

3.1. Perceived Driving Propensity. The perceived driving propensity through questionnaire survey by the response of participants directly is shown in Figure 4. Two participants exhibited perceived defensive propensity, and 14 exhibited less defensive propensity. The proportion of participants with defensive propensity was approximately 44.4%. Approximately 55.6% of the participants had a perceived aggressive propensity, with 16 and 4 corresponding to perceived less aggressive and perceived aggressive propensities, respectively.

3.2. Inherent Driving Propensity. Based on the derived inherent driving propensities from surveys of DBQ and DAS, the statistical values of each survey results from responses of all participants showed similar characteristics. Table 5 summarizes the characteristics of the two responses, and both inherent driving propensities averaged about 3.6 points, with standard deviations of 0.36 and 0.49, respectively.

3.3. Driving Behavior Characteristics. The driving behavior characteristics were analyzed, and the findings are presented in Table 6. During the driving on Section 1, the participants exhibited an average driving speed of 81.21 km/h, with the

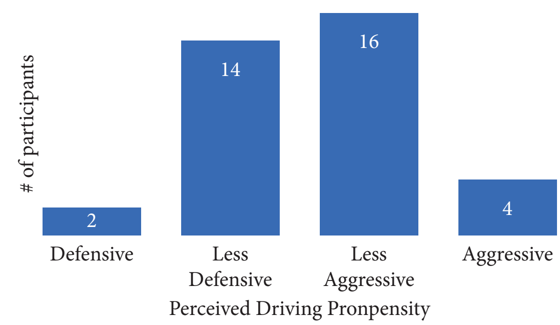

Figure 4: Response of perceived driving propensities by the participants.

Table 5: Statistic values of derived index for inherent driving propensities (1 to 5 point).

Categories	Safe driving propensities	Reckless driving propensities
Average	3.64	3.57
S. D	0.36	0.49
15pctl	3.22	3.13
85pctl	4.08	4.17

15th percentile at 76.41 km/h and the 85th percentile at 86.26 km/h, indicating a tendency to drive slightly above the road speed limit. The average distance gap was 67.66 m, with the 15th percentile at 47.09 m and the 85th percentile at 96.01 m, demonstrating a wide distribution in the spacing between vehicles. While the average longitudinal acceleration was 0.99 m/s^2, the average lateral acceleration was 2.9 m/s^2, indicating more rapid acceleration when driving in the lateral direction.

In Section 2, the average deceleration rate was −2.80 m/s^2 due to congested flow. In the congested flow situation, the average longitudinal acceleration was 1.67 m/s^2, and the standard deviation was 0.26, indicating that the participants' acceleration behavior in the section showed a similar trend. The intervehicle distance gap behavior was also shown to be 19.78 m on average and the standard deviation was 4.86, confirming that the driving behavior characteristics were limited within the congested flow.

In Section 3, the average driving speed was 58.77 km/h, and the average longitudinal deceleration and acceleration were −1.10 m/s^2 and 1.45 m/s^2, respectively. In addition, the intervehicle distance appeared to be an average of 45.24 m.

Table 6: Statistic values for main driving behavior characteristics.

Categories		Average	S. D	15pctl	85pctl
Section 1	Average of longitudinal acceleration (m/s^2)	0.99	0.45	0.53	1.55
	Average of driving speed (km/h)	81.21	4.38	76.41	86.26
	Average of intervehicle intervals (m)	67.66	21.36	47.09	96.01
	Average of lateral acceleration (m/s^2)	2.90	0.89	1.99	4.10
Section 2	Average of longitudinal deceleration (m/s^2)	−2.80	0.62	−2.28	−3.41
	Average of longitudinal acceleration (m/s^2)	1.67	0.26	1.41	1.92
	Average of intervehicle intervals (m)	19.78	4.86	15.15	25.48
Section 3	Average of driving speed (km/h)	58.77	2.93	56.46	61.09
	Average of longitudinal deceleration (m/s^2)	−1.10	0.35	−0.72	−1.47
	Average of longitudinal acceleration (m/s^2)	1.45	0.43	1.07	1.88
	Average of intervehicle intervals (m)	45.24	19.04	26.67	69.05
Section 4	Average of driving speed (km/h)	49.42	6.98	42.22	56.48

The driving behavior observed in this section indicated a departure from congested flow, resulting in an increased average driving speed, along with reduced acceleration and deceleration behaviors. Even in Section 4, the participants displayed an average driving speed of approximately 49.42 km/h, which was faster than the overall speed limit of 40 km/h.

3.4. Results of FIS

3.4.1. Results of FIS Lower Level. The inherent driving propensities, one of the lower levels of FIS, were derived by combining the previously derived safe driving propensity based on the DBQ and the reckless driving propensity based on the DAS. In terms of safe driving propensity, the groups were classified based on membership functions derived through the cluster-centroid values of k-means clustering analysis: 4.59, 4.21, and 3.75. For reckless driving propensity, values of 2.64, 3.51, and 4.16 were obtained. By applying the conditional rule that higher safe driving propensity and lower reckless driving propensity result in a more defensive driving propensity, the results were obtained as follows. Among the participants, 17 exhibited relatively defensive propensity, with 3 of them classified as showing even more defensive propensity. In contrast, 19 participants showed relatively aggressive propensity, with six of them classified as having higher levels of aggressiveness.

The remaining lower level of FIS, which is participants' driving behavior characteristics, was classified into four characteristics (defensive, moderate, less aggressive, and aggressive) based on the designed fuzzy rules. Five participants were classified as having defensive driving behaviors. In addition, 14 participants were categorized into groups displaying moderate characteristics, whereas 17 participants were assigned to groups demonstrating aggressive characteristics. Among the participants with aggressive characteristics, three exhibited even more pronounced aggressive propensity. The results are shown in Table 7.

3.4.2. Results of FIS Upper Level. Table 8 lists the comprehensive driving propensities obtained by synthesizing the results of the FIS lower level from the inherent driving propensities and driving behavior characteristics. Group 1 consisted of five participants exhibiting defensive driving propensity, whereas Group 2 comprised nine participants showing less defensive propensity. In addition, Groups 3, 4, and 5 consisted of seven participants with moderate propensity, eleven participants with less aggressive propensity, and five participants with aggressive propensity, respectively.

Using FIS, a comparative analysis was conducted to examine the differences in driving propensities among five groups defined based on the inferred comprehensive driving propensity characteristics. The average values of participant characteristics classified by groups were compared to identify differences, and statistical analysis using the Kruskal–Wallis test was performed to assess significant differences between groups. Initially, upon examining the differences in inherent driving propensities among the groups, it was observed, as presented in Table 9 and Figure 5, that the safe driving propensity did not exhibit substantial differences among the groups. The average safe driving propensity scores for Groups 1 to 4 ranged between approximately 3.6 and 3.8, while only Group 5 showed a relatively lower average score of 3.26. However, no statistically significant differences were found between the groups. In contrast, the reckless driving propensity showed statistically significant differences among the groups. It was evident that as aggressive driving propensity increased, safe driving propensity decreased, while reckless driving propensity increased.

Next, upon examining the differences in driving behavior characteristics among the groups, statistically significant differences were observed, as presented in Table 10, specifically in longitudinal acceleration, driving speed, and lateral acceleration. Groups 4 and 5, relatively classified with aggressive driving propensity, exhibited, as shown in Figure 6, rapid acceleration and deceleration, surpassing speed limits, and tended to maintain shorter intervehicle distance gap. In contrast, Groups 1 and 2, classified with defensive driving propensity, displayed driving behavior characteristics opposite to those of Groups 4 and 5.

3.5. Preferences for Automated Driving Patterns. The evaluation results of preference ranking for the five implemented automated driving patterns, ranked from 1^{st} to 5^{th}

Table 7: Results of the FIS lower level.

Inherent driving propensities					Driving behavior characteristics				
Groups	Participants	%	Average of fuzzy index	Characteristics	Groups	Participants	%	Average of fuzzy index	Characteristics
DP 1	3	8.3	0.19	Defensive	DB 1	5	13.9	0.28	Defensive
DP 2	14	38.9	0.39	Less defensive	DB 2	14	38.9	0.55	Moderate
DP 3	13	36.1	0.63	Less aggressive	DB 3	14	38.9	0.73	Less aggressive
DP 4	6	16.7	0.84	Aggressive	DB 4	3	8.3	0.89	Aggressive

Table 8: The derived comprehensive driving propensities using FIS.

Groups of comprehensive driving propensities	Participants	%	Average of fuzzy index	Characteristics
Group 1	5	13.9	0.12	Defensive
Group 2	9	25.0	0.31	Less defensive
Group 3	7	19.4	0.52	Moderate
Group 4	11	30.6	0.70	Less aggressive
Group 5	4	11.1	0.90	Aggressive

Table 9: Differences in inherent driving propensities based on the groups.

Groups of comprehensive driving propensities	Safe driving propensities		Reckless driving propensities	
	Average scores	ρ	Average scores	ρ
Group 1	3.81		3.50	
Group 2	3.68		3.27	
Group 3	3.78	0.154	3.83	0.019*
Group 4	3.60		3.62	
Group 5	3.26		4.15	

$^{*}p < 0.05$.

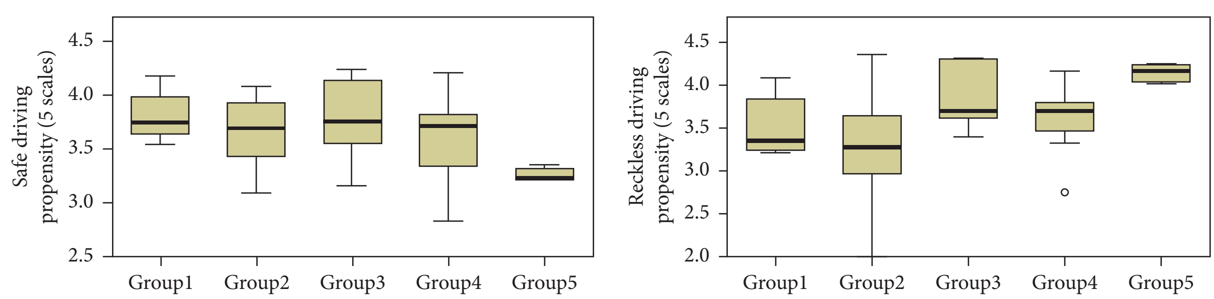

Figure 5: Distribution of inherent driving propensities based on the groups.

Table 10: Differences in driving behaviors based on the groups.

Groups of comprehensive driving propensities	Longitudinal acceleration (m/s^2)		Driving speed (km/h)		Distance gap (m)		Lateral acceleration (m/s^2)		Deceleration (m/s^2)		Driving speed on ramp (km/h)	
	A.S	ρ	A.S	ρ	A.S	ρ	A.S	ρ	A.S	ρ	A.S	ρ
Group 1	0.69		76.2		79.9		2.54		2.19		34.4	
Group 2	0.76		78.9		71.6		2.73		2.60		36.7	
Group 3	1.11	0.012*	82.3	0.003*	70.7	0.394	2.23	0.026*	2.99	0.166	42.1	0.266
Group 4	1.03		85.6		62.0		3.36		3.09		42.3	
Group 5	1.60		81.8		58.9		3.49		2.94		40.5	

A.S: average score; $^{*}p < 0.05$.

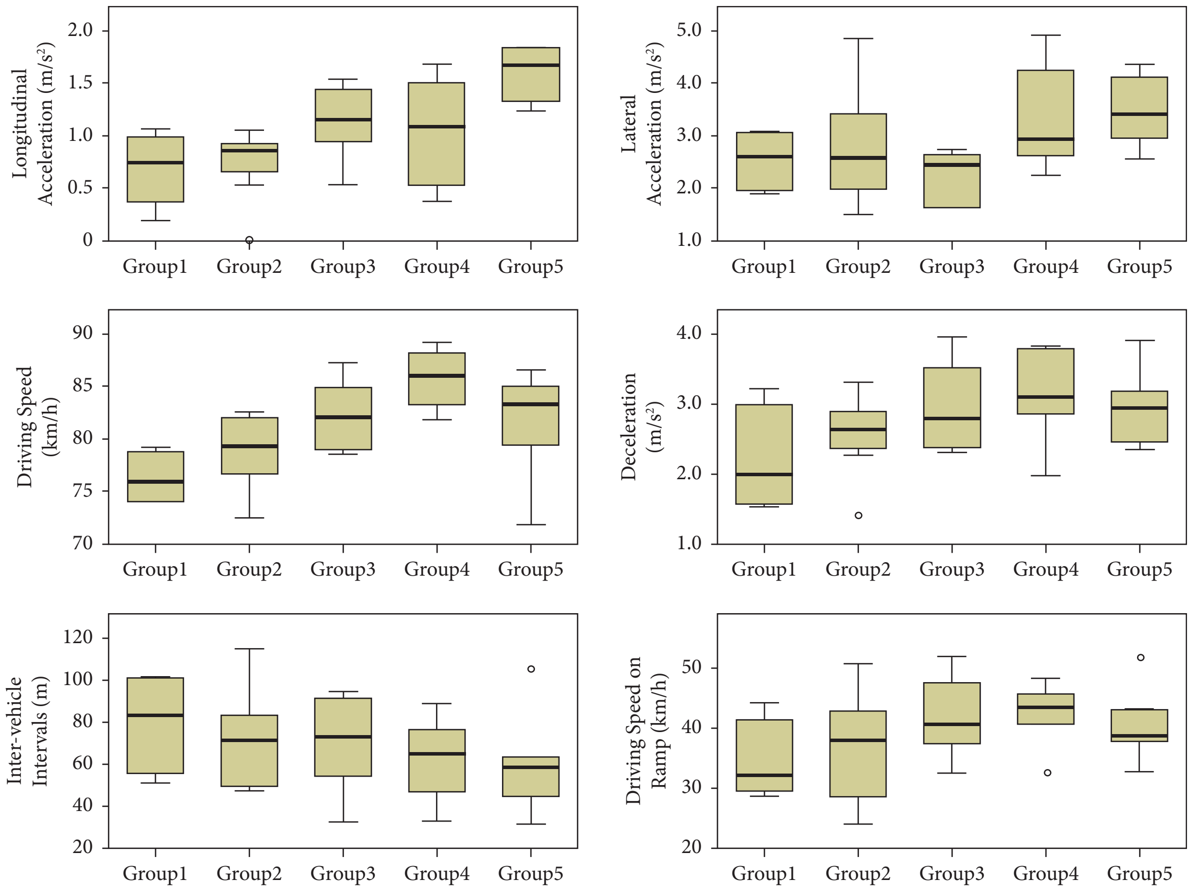

Figure 6: Distribution of driving behaviors based on the comprehensive driving propensities groups.

preference, as assessed by the participants, are presented in Table 11. The evaluation of priorities for the five automated driving patterns revealed that fourteen participants had the highest preference for the "Less Aggressive" pattern. This was followed by ten participants who prioritized the "Moderate" pattern and seven participants who preferred the "Less Defensive" pattern. In terms of second-priority preference, twelve participants favored the "Moderate" pattern, whereas eleven participants leaned towards the "Less Defensive" pattern; seven participants still showed a preference for the "Less Aggressive" pattern. Conversely, there was a low overall preference for automated driving patterns that exhibited extreme behaviors, such as "Defensive" and "Aggressive."

Utilizing the preference results of the 1st ranked automated driving pattern from the previously derived all participants' preferences, the preference trends were examined among groups based on comprehensive driving propensities inferred through FIS. It is possible to estimate the likelihood of preferring certain types of automated driving patterns based on the analyzed comprehensive driving propensity characteristics. Table 12 summarizes the preference results for the 1st ranked automated driving pattern among groups classified according to comprehensive driving propensities.

In Group 1, two participants preferred defensive automated driving patterns, whereas the remaining three preferred less defensive patterns. In Group 2, the preferences for automated driving patterns varied. The distribution of priority preferences was dispersed, with four participants having the highest preference for the less defensive pattern. Three participants preferred the moderate pattern. Moreover, there were preferences for the less aggressive and defensive patterns, with one participant each. In Group 3, the preference for the moderate automated driving pattern was relatively high; however, there was also a notable preference for the less aggressive pattern. Group 4 showed the highest preference for the less aggressive automated driving pattern, with seven participants favoring the pattern. In Group 5, three participants showed the highest preference for the less aggressive automated driving pattern. Examining the top priority preference results by group, there is a consistent tendency for automated driving pattern preference based on groups ($\gamma = 0.80$ and $p = 0.001$).

Table 11: Results of preference evaluations on the automated driving patterns.

Automated driving patterns	Preference ranking				
	1st	2nd	3rd	4th	5th
Defensive	3	1	8	13	11
Less defensive	7	11	9	8	1
Moderate	10	12	6	6	2
Less aggressive	14	7	8	7	0
Aggressive	2	5	5	2	22

Table 12: Results of selecting the top priority for automated driving patterns based on the groups.

Groups	The 1st preferred automated driving patterns					Sum
	Defensive	Less defensive	Moderate	Less aggressive	Aggressive	
Group 1	2	3	0	0	0	5
Group 2	1	4	3	1	0	9
Group 3	0	0	4	3	0	7
Group 4	0	0	3	7	1	11
Group 5	0	0	0	3	1	4
Sum	3	7	10	14	2	36

Through the results presented in Table 12, it was possible to estimate the preferred types of automated driving patterns using the comprehensive driving propensity derived through the FIS developed in this study. This result was compared with the result of preference for the 1st priority automated driving pattern based on the perceived driving propensity derived through simple questionnaire. The evaluation results for the 1st ranked automated driving preference based on perceived driving propensity are presented in Table 13.

In all four categorized propensities, there was no consistency between the perceived driving propensity and the preference of autonomous driving patterns. Among those who perceived as having a less defensive driving propensity, three participants tended to prefer relatively less defensive automated driving pattern, while seven participants favored less aggressive pattern. Among the 16 participants who perceived as less aggressive, their preferences were evenly distributed across all five automated driving patterns. The results show no significant correlation between the perceived driving propensities of the individuals and their preferred automated driving patterns ($\gamma = 0.07$, $p = 0.69$). This suggests that the acceptance of different levels of driving propensities varies according to the subjective standards set by the participants. Thus, relying on the level of driving propensities recognized by individuals as an evaluation factor has limitations in terms of objectivity.

4. Discussion

Referring to the significance of user interaction with automated driving, it was suggested that technologies based on users' trust and acceptance are needed in the process of automated driving such as motion planning and decision making [2]. To promote widespread acceptance of automated driving technology, it is imperative to implement personalized automated driving features that align with individual driving propensity [4]. Accordingly, this study was conducted from the perspective of the need for human factor research in terms of acceptance of automated driving vehicles.

For the widespread adoption of automated driving technology, it is essential to consider the potential shifts in user roles from drivers to passengers. The transition from actively driving a vehicle to passively taking automated driving may alter the user's perspective on vehicle preferences. If the decision-making process for vehicle selection has historically prioritized driving-related functions, in the era of automated driving vehicles, the emphasis may shift towards the expectation of a comfortable ride tailored to the user's preferred driving style. In addition, if human factors such as driving behaviors and propensity were previously analyzed from the driver's point of view to prevent traffic accidents and design safety facilities, other human factor studies are now needed to evaluate the acceptability and reliability of automated driving from the user's point of view. This study aims to explore the relationship between individual driving propensities and preferred automated driving patterns as crucial human factors to be considered in the era of automated driving. Consequently, the study has found two key findings as follows.

First, the study found a certain association between an individual's preferred automated driving pattern and their driving propensities. However, it was noted that the perception of one's driving propensity is subjective, and there was a lack of consistency in accepting automated driving patterns similar to their manual driving style. To derive more objective driving propensities, a comprehensive analysis of various factors is necessary. This suggests that the process of trusting and accepting automated driving from a user's perspective is influenced by complex and multifaceted factors. These factors include one's condition and usual driving behaviors, preferences, and confidence in driving, as well as differences in anxiety or comfort in an environment where direct control is not possible.

These human factors have limitations in objective evaluation due to their dependence on individual perceptions. Thus, this study employs the fuzzy logic as a method to objectively assess intricate driving propensities. The fuzzy logic demonstrates that human factors with natural language properties can be analyzed and categorized, offering a mathematical means to represent ambiguous and imprecise information. However, it is essential for the fuzzy logic to design methodologies meticulously, as results may vary depending on the reasoning process and the design of the membership function. Moreover, comprehensive research is necessary to analyze complex internal and external factors from an individual's factor, considering the impact of road traffic environments and vehicle specifications on human factors, particularly in relation to ride comfort.

Second, automated driving behaviors based on user propensity need to be carried out in decision making such as motion planning and gap acceptance. The participants in the study demonstrated clear preference differences for five automated driving patterns, which were set as a difference in acceleration of about 0.5 m/s^2 intervals, a difference in

Table 13: Evaluation results of preferred automated driving patterns according to perceived driving propensities.

Perceived driving propensities	The 1st preferred automated driving patterns					Sum
	Defensive	Less defensive	Moderate	Less aggressive	Aggressive	
Defensive	1	0	1	0	0	2
Less defensive	0	3	4	7	0	14
Less aggressive	2	3	4	5	2	16
Aggressive	0	1	1	2	0	4
Sum	3	7	10	14	2	36

driving speed of 5 km/h intervals, and a difference in intervehicle headway of 20 m intervals. It was observed that various factors, such as driving time, lane-changing and overtaking behaviors, acceleration and deceleration levels, driving stability, and similarity to one's own driving style, influenced the preference ratings depending on the participants' driving propensities. This suggests that an individual has a preferred method for automated driving patterns, highlighting the importance of implementing automated driving in accordance with their preferences throughout various driving processes to achieve high reliability and acceptability.

5. Conclusion

This study aimed to analyze preferences of automated driving patterns from the user's perspective, based on their driving propensities. It emphasized the necessity of studying human factors to prepare for the era of automated driving and to implement automated driving patterns that align with user preferences. To achieve this, inherent driving propensities were derived from surveys and driving behaviors based on a driving simulator, categorized through FIS. This allowed for a more objective determination of individual driving propensity related to acceptable automated driving patterns. Furthermore, this study involved analyzing actual driving behaviors of the participants, focusing on acceleration, deceleration, lane change, and overtaking during road driving. By implementing these driving behaviors in five different styles of automated driving patterns, characteristics of preferred automated driving patterns were identified according to their driving propensities.

The main implications of this study are as follows. The preferred automated driving patterns, as perceived by the participants, exhibited inconsistency based on their perceived driving propensities. The subjective nature of this preference made it challenging to objectively accept the recognized driving propensities. Thus, the study highlighted the need for research on standards that can objectively assess users' driving propensities to develop automated driving technology that meets users' preferences and acceptance.

Moreover, this study found that preferences for automated driving patterns varied based on the type of driving propensities. The FIS-based classification method presented in this study effectively revealed consistent trends in preferred automated driving patterns. Specifically, participants with relatively passive driving propensities preferred automated driving patterns with passive driving behaviors, while those with aggressive driving propensity preferred patterns with aggressive behaviors. The results further suggested that individuals with passive propensity preferred safer driving patterns and demonstrated greater sensitivity to perceived threats and anxiety. In contrast, aggressive individuals preferred faster driving and were more resistant to slower driving patterns. Accordingly, to enhance the acceptability of automated vehicles from the user's perspective, there is a need for technological development that can be tailored to individual propensity and preferences in the process of implementing automated driving patterns.

Nevertheless, it is important to acknowledge certain limitations of this study. First, the use of a driving simulator to assess driving behaviors and preferred automated driving patterns introduces a constraint in that it may not fully replicate real-world driving conditions because of the inherent characteristics of the virtual reality environment. In addition, the absence of a motion function in the driving simulator restricts the evaluation of the actual experience and the impact of riding on the implemented automated driving patterns. Moreover, the study focused solely on driving behaviors and preferred automated driving patterns within a limited road environment, specifically on urban highways. Consequently, the potential variations that may arise in different driving environments were not fully considered. These limitations should be considered when interpreting the findings of this study. Future research should address these constraints by incorporating more realistic driving simulations and encompassing diverse driving environments to obtain a more comprehensive understanding of users' preferences and driving propensities in relation to automated driving technology.

To facilitate future research advancements, passenger-related factors, such as ride comfort and motion sickness, must be evaluated when implementing and assessing automated driving behaviors using driving simulators. Considering that ride comfort resulting from vehicle movements can affect preference evaluations, it is crucial to incorporate this aspect into future studies. Moreover, it is essential to account for variations in driving behaviors and preferred automated driving patterns that may emerge in diverse road traffic environments, including urban roads and nonsignal intersections, rather than solely focusing on continuous traffic flows. In addition, continuous research efforts should be directed towards refining the classification of driving propensities to establish more objective criteria for deriving driving propensities, thereby allowing for more advanced insights into human factors and automated driving. By addressing these aspects, future research can yield enhanced outcomes in the realms of human factors and automated driving.

Data Availability

The data supporting the conclusions of this article can only be made available for academic research. Requests to access the datasets should be directed to tseven37@naver.com.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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