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Study on the Take-over Performance of Level 3 Autonomous Vehicles Based on Subjective Driving Tendency Questionnaires and Machine Learning Methods

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Abstract
Level 3 autonomous vehicles require conditional autonomous driving in which autonomous and manual driving are alternately performed; whether the driver can resume manual driving within a limited time should be examined. This study investigates whether the demographics and subjective driving tendencies of drivers affect the take-over performance. We measured and analyzed the reengagement and stabilization time after a take-over request from the autonomous driving system to manual driving using a vehicle simulator that supports the driver's take-over mechanism. We discovered that the driver's reengagement and stabilization time correlated with the speeding and wild driving tendency as well as driving workload questionnaires. To verify the efficiency of subjective questionnaire information, we tested whether the driver with slow or fast reengagement and stabilization time can be detected based on machine learning techniques and obtained results. We expect to apply these results to training programs for autonomous vehicles' users and personalized human–vehicle interfaces for future autonomous vehicles.

KEYWORDS
autonomous driving, driving tendency, *k*-nearest neighborhood, take-over performance, take-over request

1 | INTRODUCTION

An autonomous vehicle can drive itself without the manual operation of a human driver. The Society of Automotive Engineers (SAE) J3016 [1] classifies autonomous vehicle types from SAE Level 0 (no automation) to SAE Level 5 (full vehicle autonomy), according to their degree of autonomy. Figure 1 shows the level of automation of autonomous vehicles [2].

The driver's role depends on the level of autonomous driving. The driver's role is emphasized at Level 3 and below; nevertheless, no driver intervention is needed at Levels 4 and above. In a Level 3 autonomous vehicle, driving is conditionally autonomous; the autonomous driving and manual driving modes exist alternately. The autonomous driving system (ADS) drives in the autonomous driving mode. However, in the manual driving mode, the driver must operate the vehicle.

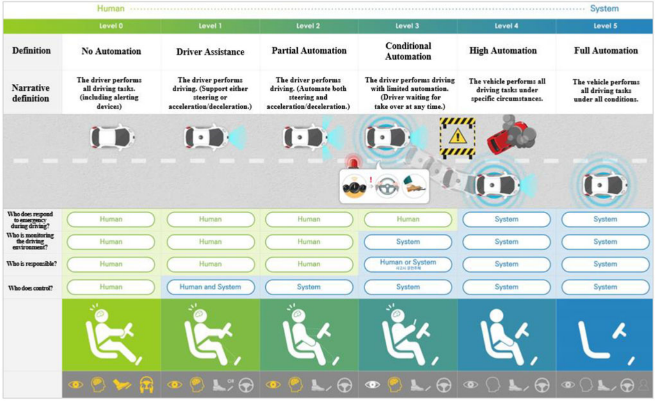

FIGURE 1 Levels of autonomous vehicles. (Modified pictures of KOTSA [2], after receiving written permision from author)

Accordingly, a control authority transition for transferring the right to handle the vehicle occurs between the ADS and human drivers in a Level 3 autonomous driving vehicle. When control is transferred from the driver to the ADS, the control authority transition process is performed stably; conversely, an accident could occur when control is transferred from the ADS to the driver. In the autonomous driving mode, the driver may be occasionally immersed in nondriving-related tasks (NDRTs) instead of concentrating on the driving situation, exposing the driver to risks during the process of a control authority transition that requires the driver's manual intervention. This could lead to accidents. Thus, drivers operating Level 2 and 3 autonomous vehicles must be "fallback-ready users" who can initiate a manual operation at any time upon request by the ADS.

In 2018, the driver of a Tesla vehicle operating in the autopilot mode died in a crash while playing a smartphone game. At that moment, the driver did not have to drive the car because the ADS was driving the car. Based on an investigation, the US National Transportation Safety Board (NTSB) announced lack of driver status monitoring during autonomous driving as one of the major causes of vehicular accidents. The NTSB presented nine new safety recommendations to the National Highway Traffic Safety Administration, including the following two recommendations related to driver monitoring systems [3].

- For vehicles equipped with Level 2 automation, SAE international should develop performance standards for driver monitoring systems to minimize driver disengagement, prevent automation complacency, and account for foreseeable misuse of automation.
- After developing the performance standards for driver monitoring systems recommended in safety recommendation H-20-X, all new passenger vehicles with Level 2 automation should be equipped with a driver monitoring system that meets these standards.

The driver's ability to drive manually in Level 3 autonomous vehicles may deteriorate if the ADS drives more often than the human driver. ISO/PDTR 21959 proposes considering time- and quality-related performances for control authority transition from an autonomous vehicle system to a human driver [4]. When a request to start manual driving is made, the driver can recognize this and react reflexively, such as by raising his head to look ahead or putting down an object in hand. Subsequently, the driver may put a hand on the steering wheel, move the foot onto the accelerator, or operate a paddle-shift to transition to manual driving. After a driver switches from autonomous to manual driving, a certain amount of time is required to attain a stable level of manual driving, such as driving a Level 0 vehicle. The time-related performance can be determined by measuring the time at which the driver first responds to a take-over request (TOR), time at which the driver must reengage in manual driving, and the stabilization time associated with manual driving. The quality-related performance can be measured based on the distance to other vehicles, standard deviation of the steering wheel angle, longitudinal/lateral acceleration values, and brake frequency after the driver starts manual driving.

Reducing the reaction time for TOR, a time-related performance measure, is closely linked to reducing accidents that occur when transferring control. Various previous studies have aimed to improve the time performance. The provision of driving situation information was studied by Kim and others [5], and Kim and others [6] investigated a way of providing precue before initiating TOR. Cunninghama and Regana [7] examined the modality of an interactive device to provide a TOR, whereas Kim and others [8] and Endsley [9] studied the effects of driver readiness. The results of the previous studies can be linked to functions that could be included in designing an autonomous vehicle system capable of quickly recognizing TOR information and reducing the reaction time. Some studies [10,11] confirmed that time performance was improved by reducing the TOR reaction time through experience and learning. Female drivers had a lower time performance rate than male drivers, and middle-aged drivers had a lower time performance rate than younger drivers. Nevertheless, even if the driver is engaged in various NDRTs, including conversation, drinking, and texting, repeated control transition leads to a gradual improvement in performance. We infer that education and training on using Level 3 vehicles are necessary for the regular use of these vehicles.

There has been no research on predicting control transfer performance by collecting driver characteristic information in advance and knowing whether education or training is required. Hence, research is required to analyze how driver characteristics affect control authority transition performance. This study aims to determine whether the driver's subjective information collected through the prequestionnaire, such as demographic characteristics, driving workload weight information, speed driving, and wild driving tendencies, affects control authority transition performance. Moreover, the following research questions are presented to verify the efficiency of subjective tendency and check whether it could distinguish between a slow and high control performance driver before using a Level 3 vehicle.

- *Research Question 1*. Does the driver's subjective tendency affect the reengagement time of manual driving? Can the driver's prequestionnaires be used to classify fast and slow transition drivers?
- *Research Question 2*. Does the driver's subjective tendency affect the manual driving stabilization time? Can fast and slow manual driving stabilization time drivers be classified using the drivers' prequestionnaires?

The remainder of the paper is organized as follows. Section 2 examines the related studies on the human factor characteristics of autonomous vehicles. Section 3 describes the experimental environment for control transition using the vehicle simulator, subjective driving tendency questionnaire contents, experimental procedure, and transition time measurement method. Section 4 describes the statistical analysis results on the information collected by the control authority transition experiment. Section 5 explains the method and results of classifying drivers who respond quickly or slowly to the control authority transition based on the subjective driving questionnaires. Finally, Section 6 presents the conclusion and future work.

2 | RELATED STUDIES

Previous research regarding the human factor characteristics associated with autonomous driving includes driver's inattention and distraction, situational awareness (SA), excessive trust and belief in autonomous vehicles, and poor manual driving skills [12]. The driver, immersed in NDRTs instead of driving, could be inattentive and distracted when the ADS is driving. Thus, when a request to switch to manual operation occurs, the response time increases, thereby deteriorating driving performance [13].

SA is the consciousness of events that occur in the surrounding environment as spatiotemporal environmental factors; it understands the environmental factors and predicts the near-future driving environment [14,15]. If the driver is distracted or inattentive during autonomous driving, the SA level deteriorates because the driver is not focusing on maintaining awareness related to vehicle and road conditions [16]. A dangerous situation can occur if the system warning is unexpectedly generated when the SA level is reduced [17,18]. Kim and others [5] stated that the overall control authority transition performance improved when the driving situation information was provided to the terminal installed in the vehicle compared with when the driving situation information was not provided. Even if the driver performs a secondary task (NDRT), the driver can recognize this if the information, such as the remaining time and distance until a TOR, is represented through the agent terminal mounted on the vehicle. The SA information helps to prepare for the transfer of control authority in advance.

Kim and others [19] stated that the drivers performed an NDRT with high visual and high auditory workloads. An image was displayed on the vehicle terminal to increase the visual workload, and the experimenter was guided to find and click other parts. To increase the auditory workload, an *n*-back test was conducted by continuously calling a number. A response was achieved by adding the previous number to the heard number. According to the NDRT performed by the driver during autonomous driving, the driver's visual, auditory, cognitive, and psychomotor workload may vary, and the results affect the control transition performance. Precues, such as the "beep" sound, which induces attention in advance, increase the relevant baseline activity before the stimulus occurs. An increase in basal activity improves the performance and efficiency of subsequent tasks [20]. Additionally, precue induces early perceptual processing, which gets the person cognitively ready [21]. A precue causes attention shift, which increases the processing efficiency. Thus, providing a precue before TOR may reduce response time. Kim and others [6] demonstrated that the three types of precues were provided 4 s before TOR. Visual channel precue was provided using repeated display while monophonic and repeated sounds represented auditory channel. It was suggested that the control right transition performance was better in providing auditory monophonic or repetition than visual. Cunninghama and Regana [7] investigated how to employ the modality of the interaction device that provides TOR to reduce the reengagement time of manual driving. TOR information was provided by combining two or three modalities among visual, auditory, and tactile information. The results suggest that control transition response performance significantly improved when TOR notification was provided by adding tactile modality. Driver readiness should be considered a human factor that affects control transfer performance. Driver readiness is a driver's state indicating whether the driver can manually operate the vehicle by regaining control when control is transferred from the autonomous to manual driving mode [4]. When the driver was nonoverloaded or immersed in NDRT, the driver's readiness decreased and manual driving could be dangerous. Kim and others [22] stated that a system design method for measuring driver readiness was proposed. Some studies [8,9] measured the questionnaire-based subjective driving readiness. They demonstrated that driver's readiness negatively correlated with reengagement time but positively correlated with the vehicle control quality. Kim and others [23] presented a study on the correlation between the subjectively felt workload and control transition response time.

Previous studies investigated how the control right transition performance can be improved through various methods, such as observing driving readiness, providing SA and precue information before TOR, and providing TOR using the multimodal approach. However, no study predicts control transition performance using driver's subjective tendency information obtained from prequestionnaires. This study predicts whether the driver's control transition and manual driving stabilization performances are fast or slow using the driver's demographics, speed driving and wild driving tendency, and driving workload weight information. These predictions could be used for providing education to first-time drivers regarding Level 3 autonomous vehicles.

3 | EXPERIMENTS

3.1 | Configuration of the experimental environment

We conducted experiments using a stationary vehicle simulator built on the Hyundai Click vehicle model with driver-controlled motion capabilities (Figure 2). We built a vehicle simulator to obtain a 135° horizontal field of view (FOV) using three monitors (43 inches each) to simulate driving on a real road. Each monitor displayed the left lane, front road, and right-side view. The side- and rear-view mirrors were mounted for rear road scenes with horizontal and vertical 20° and 25° FOVs, respectively. The experimental road screen was an eight-lane two-way (four lanes in each direction) highway environment. The test vehicle where the driver was boarded was placed on the third lane (out of the four lanes). It maintained a traffic density of approximately 20 vehicles in a 1-km section, including the front, left (second lane), and right lanes (fourth lane).

The vehicle simulator was wired or wirelessly connected to a motion sensor, image sensor, eye tracker, and monitoring system that visually synchronizes and collects the information for the reaction of the experimental driver. The vehicle, environment, and driver behavior information collected in the experiment are presented in Table 1. The collected information is transmitted and saved to the data acquisition server. The temperature and humidity of the laboratory remained constant [5,7–9,23].

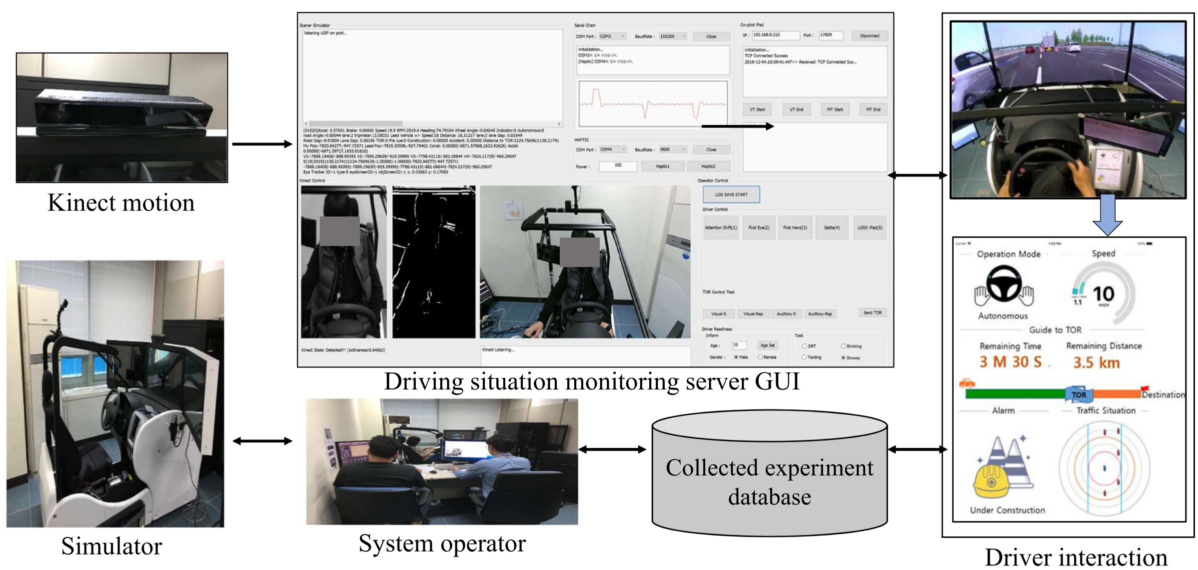

FIGURE 2 Experimental environment [5,7–9,23]

TABLE 1 Acquisition data

Items	Measurement method	Device
Motions	A Kinect device for motion detection is installed in front of the vehicle simulator, and the driver's motion is measured	Kinect
Video	Attach a camera to the top frame of the vehicle simulator and capture the simulation front screen video from the driver's viewpoint	Camera 1
	From the start to the end of the experiment, sit in the simulator vehicle and take pictures of the driver performing the experiment	Camera 2
	Driver's frontal image captured by Kinect equipment installed in front of the vehicle simulator	Kinect
Eye tracking	Install eye trackers on the left and right corners of the dashboard of the vehicle simulator and measure the driver's gaze information	Eye tracker
Vehicle information	Speed, RPM, distance to the vehicle ahead, lane information, and vehicle position in the lane	Vehicle simulator
Driving environment information	Vehicle location, surrounding vehicle information (front, rear, and side)	Vehicle simulator

3.2 | Preliminary questionnaire information

Some emotions always accompany human behavior manifested through intense mental/physiological changes. Aggression is one of the innate traits in drivers; it is unpredictable during the driving phase and often occurs characteristically [24].

A driver's aggressive road behavior could lead to dangerous situations, such as breaking the speed limit, not maintaining a safe distance from the vehicle in front, or making a sudden lane change. The more aggressive drivers are, the more careful they should be to avoid accidents. Driver's aggressiveness information is a subjective characteristic. It is difficult to quantify; thus, it is not easy to know the driving tendency information completely. In the traffic psychology field, drivers' driving manners are judged through a questionnaire related to driving behavior. Although a driver's unique behavior could be evaluated, it depends on the questionnaire filled, which could be subjective.

Based on the study conducted by Reason and others [25,26], the driver behavior questionnaire (DBQ) was modified according to the circumstances of each country. In Netherlands, there have been studies using DBQs to develop driver behavior models for accident causes [27].

In a study conducted in Korea, risk driving behavior factors were categorized into speeding, inexperienced coping, wild/rough driving, drunk driving, and distraction. A questionnaire was used to measure these five factors, and research results that could identify aggressive drivers with high accident rates in advance were published [28]. The results showed the highest positive correlation between speeding and wild driving among the five factors. In a recent study of a traditional vehicle that requires human drivers, high-risk and low-risk groups were classified using the *K*-means cluster analysis method based on the risky driving behavior questionnaire measurement information on the driver's psychological characteristics and attitudes [29].

In a Level 3 vehicle, the ADS and human driver take turns for driving the vehicle; therefore, reducing the risk of traffic accidents caused by the human driver should be considered. Hence, there is a need for a method to identify drivers who need training in advance so that when a human driver uses a Level 3 vehicle, the reaction time for TOR and manual driving stabilization time can be shortened. It is necessary to determine the relationship between the driver's subjective tendency and the performance of the control authority transition through the questionnaire. In this study, a questionnaire was administered focusing on driver's demographics, speed driving, and wild driving tendency information. As switching from autonomous driving to manual driving increases the driver's driving workload, weight information on factors determining driving workload using NASA-TLX was included in the questionnaire. Table 2 presents the questionnaire items used.

3.3 | Experimental procedure

Herein, the experiments were conducted with the approval of the Korean Public Institutional Bioethics Committee (http://public.irb.or.kr/, approval number P01-202009-13-001). We used a simulator that provides a voice command, such as "Drive manually" after ∼3 min

TABLE 2 Description of questionnaire features

Feature group	Detailed features	Questionnaires	Score
Demographic information	Age	Age	Young/middle
	Gender	Gender	Man/woman
	D_Exp	Driving experience	Years of experience
Speed driving tendency	Pleasure	The more I speed it up, the more pleasure I get.	1–7
	Stress	When I drive at high speed, I relieve my stress.	1–7
	Impatience	I tend to drive hastily.	1–7
	S_Compliance	Obeying the speed limit will impede the flow of traffic.	1–7
	Flexibility	Driving below the speed limit on the highway is not flexible.	1–7
	Accident	I have heard from people around me that I tend to drive as if an accident will happen.	1–7
	Q_Start	I get ahead of other cars when I start after the signal changes.	1–7
	S_Increase	Driving speed on Korean roads should be higher than it is now.	1–7
Wild driving tendency	Y_Operation	When I drive, I do not yield my lane well.	1–7
	Concession	I lack concessions when driving.	1–7
	A_Interrupt	I get angry with the driver who cuts in next to me.	1–7
	Irritability	I get angry when I get caught at a stop sign while driving.	1–7
	Slow_Angry	When I see the driver of a slow-moving car, I get angry.	1–7
	A_Stop	When I drive, I make a sudden start or a sudden stop.	1–7
	Rest area	I think it's a waste of time to stop by a rest stop when I'm tired.	1–7
	No_Concessions	I do not yield when another vehicle cuts in.	1–7
Driving workload weight [30]	Mental burden	I have a mental burden when driving.	0–5
	Physical burden	I have a physical burden when driving.	0–5
	Time burden	I feel a time burden when driving.	0–5
	Achievement	I want to be able to drive and perform well.	0–5
	Effort	I try to drive well.	0–5
	Frustration	I feel frustrated because of irritability or anxiety when driving.	0–5

of autonomous driving. At this time, the driver must manually operate the steering wheel, brake, or accelerator to start manual driving. When manual driving starts, the operation mode information is displayed as "manual mode" on the display screen mounted on the right terminal in Figures 2 and 3. When the experimental driver arrives at the laboratory, they are informed about the purpose and precautions of the experiment and given a consent form that needs to filled for their participation in the experiment. Only those who sign the agreement can participate in the experiment. Drivers fill out a questionnaire, as shown in Table 2, in advance, including demographic information (gender, age, and driving experience), speed and wild driving tendencies, and driving workload information. After completing the preliminary questionnaire, the experiment operator explains the autonomous and manual driving guidelines as well as guides the drivers to become familiar with the simulated driving and control-switching method. Upon completing the practice, the autonomous driving experiment is conducted after confirming that there is no dizziness or motion sickness due to the use of a simulator. Autonomous driving begins when the experiment starts; therefore, drivers were instructed to perform NDRTs with their smartphones to retrieve information or text. After ∼3 min of autonomous driving, the ADS will request a control switch with the instruction "Please drive manually." The driver starts manual driving and operates the simulator vehicle. When the driver gets used to driving, the display says "it is stable" to the operator. Then, the driver continues manual driving. When the manual operation time exceeds ∼2 min and 30 s, the operator tells the driver "I will end the experiment" and stops the simulator operation. After the experiment, the driver fills out a postquestionnaire regarding their experiment experience.

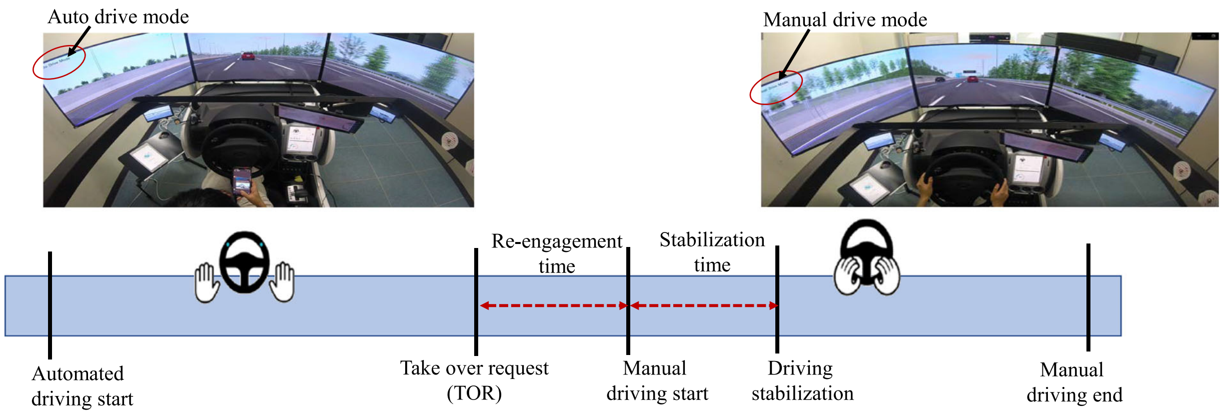

FIGURE 3 Concept of control authority transition time

3.4 | Measurement of control authority transition time

We measure a driver's control authority transition performance in two ways: the reengagement and stabilization time. As the experiment starts in the autonomous driving state, the driver can freely perform NDRT, such as web search or text message using their smartphone. When the TOR "Please drive manually" occurs, the driver hears the TOR and responds reflexively, such as raising his eyes and looking around. Then, the driver puts their hand on the steering wheel or manually operates the brake or accelerator to regain control of driving from automatic driving to manual driving. We measured the time for the driver to start manual driving after TOR and denoted it as the reengagement time. After the driver starts manual driving, the driver says "stable" when they get used to the driving operation. We measured the time until the driver says "stable" after starting manual driving and denoted it as stabilization time. Figure 3 shows the concept of the control authority transition time.

4 | STATISTICAL ANALYSIS

4.1 | Data preprocessing

The experiment involved 120 people; however, three people's data could not be used for statistical analysis due to errors. For example, one participant unexpectedly delayed the operation of the vehicle simulator due to their lack of experience in operating the vehicle simulator, one participant could not achieve stable manual operation, and one participant made an error in the input value. Table 3 shows a summary of the data of 117 people without errors. The average reengagement time for manual operation was 4.84 s, and the average manual operation stabilization time was 13.27 s. We conducted outlier processing on these data, removing values beyond three times the standard deviation. The final 114 data values were used for analysis. Finally, the drivers' age groups comprised 56 young drivers in their 20s and 30s and 58 middle-aged drivers in their 40s and 50s. Based on gender, there were 70 male and 44 female participants.

4.2 | Statistical analysis in reengagement time

To safely use a Level 3 autonomous vehicle, whether the driver can initiate manual driving within a limited time must be examined. For example, in Germany's Federal Highway Research Institute study [31], the manual driving reengagement time was proposed to be 4 s. Research on an appropriate threshold for manual driving reengagement time after TOR should be conducted continually; driver characteristics may vary between countries. In this study, based on the reengagement time average in Table 3, we classified the driver who quickly regained control within the threshold (fast class) and those who exceeded the threshold (slow class). Additionally, we analyzed each group. We denote the drivers who performed manual driving reengagement quickly as $\text{Fast}_{\text{reeng}}$ and those who performed slowly as $\text{Slow}_{\text{reeng}}$.

According to the statistical analysis results obtained per class based on the reengagement time presented in Table 4, 39.3% and 60.7% of the female drivers were in the $\text{Slow}_{\text{reeng}}$ and $\text{Fast}_{\text{reeng}}$ classes, respectively. For male drivers, the $\text{Slow}_{\text{reeng}}$ and $\text{Fast}_{\text{reeng}}$ classes accounted for 44.8% and 55.2%, respectively. A higher percentage of male drivers exhibited slower control transitions than

TABLE 3 Statistical analysis result of control authority transition time

Performance	N	Mean	Min	Max	SD	Q1	Q2	Q3
Reengagement	117	4.84	1.89	11.46	1.51	3.75	4.74	5.70
Stabilization	117	13.37	2.28	107.06	13.46	6.51	9.66	12.81

Abbreviations: Q, quantile; SD, standard deviation.

TABLE 4 Statistical analysis based on reengagement time

		Gender		Age		
Class	Count	Woman	Man	Young	Middle	Exp.
$Slow_{reeng}$	48	22 (39.3%)	26 (44.8%)	19 (33.9%)	29 (50%)	16.1
$Fast_{reeng}$	66	34 (60.7%)	32 (55.2%)	37 (66.1%)	29 (50%)	13.7
Sum	114	56 (100%)	58 (100%)	56 (100%)	58 (100%)	-

Abbreviation: Exp., average driving experience (years).

female drivers. In case of young drivers, the $Fast_{reeng}$ class percentage was 66.1% and the $Slow_{reeng}$ class rate was 33.9%, indicating that younger drivers physically proceed with manual driving reengagement faster. In middle-aged drivers, the $Slow_{reeng}$ and $Fast_{reeng}$ class percentages were identical.

The statistical analysis results in Table 4 showed that the reengagement time in manual driving differs among drivers. To determine whether groups determined to be slow and fast based on their reengagement times have the same average value in the questionnaires specified in Table 2, we established the following null and alternative hypotheses and conducted an independent sample *t*-test.

- *Null hypothesis*: The average value obtained through questionnaires for the drivers exhibiting slow reengagement is equal to that of the drivers exhibiting fast reengagement.
- *Alternative hypothesis*: The average value obtained through the questionnaires for the drivers exhibiting slow reengagement is different from that of the drivers exhibiting fast reengagement.

Table 5 presents the features in the questionnaires with *p*-values below a significance level of 0.1 after conducting an independent sample *t*-test. The average value obtained based on the speeding tendency questionnaire information of the $Fast_{reeng}$ class was larger than that of the $Slow_{reeng}$ class. Based on the speed driving tendency questionnaire information presented in Table 5, the average values of Pleasure, Stress, Impatience, Accident, Q_Start, and S_Increase questionnaire scores in the $Fast_{reeng}$ class were significantly higher than those in the $Slow_{reeng}$ class ($p < 0.05$). These observations confirmed that the speed driving tendencies of drivers who achieved manual driving reengagement quickly were "the higher the speed, the greater the enjoyment," "the higher the speed, the less the stress," and "they drive impatiently." We also observed from the independent sample *t*-test results that such drivers tend to hear from people around them about the likelihood of an accident. Further, they tend to either outrun other cars when they start to drive after the signal changes or believe that the road speed should be higher than the existing speed limit. There was no significant difference in the S_Compliance and flexibility questionnaire items ($p > 0.05$).

In the wild driving tendency questionnaire information, the questionnaire value of the fast class drivers was significantly higher than that of the slow class drivers in irritability ($p < 0.05$) and Slow_Angry items ($p < 0.1$). These results showed that the drivers in the $Fast_{reeng}$ class tend to get angry when they are caught at a stop sign while driving or when they see the driver of a slow-moving car. There was no significant difference in the Y_Operation, Concession, A_Interrupt, A_Stop, Rest area, and No_Concessions questionnaire items. Although the *p*-value is not significant, the shorter the reengagement time, the larger the questionnaire value in the following items: "I do not yield my lane well while driving," "I get annoyed when I meet a stop sign while driving," "I get angry when I see a slow-moving car," "I make a sudden start or stop," and "I do not yield when another vehicle cuts in."

In the driving workload-weighted questionnaire information, the average questionnaire value of the drivers with the fastest reengagement time was

TABLE 5 Independent sample t-test results for the questionnaire in the groups divided by reengagement time

Feature group	Detailed features	Average in $Fast_{reeng}$	Average in $Slow_{reeng}$	p-value (two-sided)
Speed driving tendency	Pleasure	4.67	3.98	0.017*
	Stress	4.24	3.65	0.045*
	Impatience	3.59	3.00	0.050*
	Accident	2.44	1.90	0.025*
	Q_Start	3.21	2.54	0.016*
	S_Increase	3.89	3.23	0.037*
Wild driving tendency	Irritability	3.44	2.69	0.005*
	Slow_Angry	3.73	3.23	0.079**
Driving workload weight	Mental burden	1.56	1.96	0.090**
	Time burden	3.00	2.54	0.050*

**$p < 0.1$. *$p \leq 0.05$.

TABLE 6 Statistical analysis based on stabilization time

		Gender		Age		
Class	Count	Woman	Man	Young	Middle	Exp.
$Slow_{stab}$	30	20 (35.7%)	10 (17.3%)	11 (19.6%)	19 (32.8%)	17.1
$Fast_{stab}$	84	36 (64.3%)	48 (82.8%)	45 (80.4%)	39 (67.2%)	13.9
Sum	114	56 (100%)	58 (100%)	56 (100%)	58 (100%)	-

Abbreviation: Exp., average driving experience (years).

significantly larger in the mental burden ($p < 0.1$) and time burden ($p < 0.05$) questionnaires. Although the independent sample t-test result was not significant, the time to reengage in manual driving was observed to be faster in drivers who tend to have a physical burden while driving, who try to drive well, and who felt frustrated due to irritability or anxiety while driving.

4.3 | Statistical analysis in stabilization time

By setting the average stabilization time as threshold, as shown in Table 3, we classified drivers into two groups: $Fast_{stab}$ and $Slow_{stab}$. We also analyzed the characteristics of human factors in each group. The statistical analysis results in Table 6 showed that 35.7% and 64.3% of female drivers were in the $Slow_{stab}$ and $Fast_{stab}$ classes, respectively. For male drivers, the $Slow_{stab}$ and $Fast_{stab}$ classes accounted for 17.3% and 82.8%, respectively. Hence, the male drivers stabilized faster after they started to drive manually, as compared with female drivers. For young drivers, the $Fast_{stab}$ and $Slow_{stab}$ class percentage rates were 80.4% and 19.6%, respectively. Among the middle-aged drivers, the percentage of the $Fast_{stab}$ class and $Slow_{stab}$ class was 67.2% and 32.8%, respectively. It means that younger drivers could get used to the vehicle operation physically faster after starting manual driving than middle-aged drivers. Therefore, they can drive the vehicle more reliably in operations such as lane keeping and vehicle speed control.

Similar to the statistical analysis for the two groups of drivers divided by their reengagement time, we conducted an independent sample t-test for the average equality of each questionnaire item in two groups of drivers based on the stabilization time. Table 7 presents the features in the questionnaires with p-values below the significance level of 0.1.

Manual driving stabilization refers to a condition where the vehicle can be driven more stably, such as lane keeping, distance from the vehicle in front, and vehicle speed control. In the speed driving tendency questionnaire information presented in Table 7, the average values of "Stress," "S_Compliance," "Flexibility," and "S_Increase" questionnaire scores of the drivers in $Slow_{stab}$ were significantly higher than those of the $Fast_{stab}$ drivers ($p < 0.1$). Drivers who prefer speeding were analyzed as $Slow_{stab}$, as they take longer to stabilize. $Slow_{stab}$ drivers have a strong tendency to think that

TABLE 7 Independent sample t-test results for the questionnaire by the stabilization time group

Feature group	Detailed features	Average in $Fast_{stab}$	Average in $Slow_{stab}$	p-value (two-sided)
Speed driving tendency	Stress	3.85	4.40	0.095**
	S_Compliance	2.73	3.33	0.070**
	Flexibility	3.94	4.67	0.064**
	S_Increase	3.45	4.07	0.086**
Driving workload weight	Time burden	2.95	2.40	0.038*

**$p < 0.1$. *$p \leq 0.05$.

"high-speed driving relieves stress," "obeying the speed limit disrupts the flow of traffic," and "on the highway, driving below the speed limit is inflexible, and the driving speed should be higher."

The average values of the drivers in $Slow_{stab}$ were larger than that of the drivers in $Fast_{stab}$ based on the eight features of the questionnaire information of wild driving tendency; nevertheless, the independent sample t-test was not significant. In the driving workload weight, the average value of the questionnaire information showed a significant difference only in the time burden questionnaire ($p < 0.05$). It has been observed that drivers who consider time burden important show faster stabilization.

4.4 | Correlation analysis

In this section, we outline the correlation analysis of features in the questionnaire and class variable configured by the reengagement or stabilization time. The class variable was set as 1 for drivers belonging to $Fast_{reeng}$ and $Fast_{stab}$ and 0 for drivers belonging to $Slow_{reeng}$ and $Slow_{stab}$. Table 8 summarizes the correlation coefficients between features in the questionnaire and class variables. Features that showed a correlation lower than 0.05 with the reengagement class variable were "Gender," "Concession," "A_Interrupt," "Physical burden," "Achievement," and "Effort features." Some features that showed a correlation lower than 0.05 with the stabilization class variable were "Impatience," "Concession," "A_Interrupt," "Rest_Area," "Mental burden," and "Frustration." Gender feature was associated with stabilization time, whereas age and driving experience correlated with reengagement class and stabilization class variables. It was observed that overspeeding and rough driving tendencies were more related to both class variables. Drivers who valued their driving time burden correlated more positively with faster reengagement and stabilization time.

5 | CLASSIFICATION ANALYSIS

5.1 | Classification model creation and prediction method

Before using a Level 3 autonomous vehicle, if it is possible to predict drivers with slow reengagement and slow stabilization time using questionnaires, such as drivers' demographics and driving tendencies information, vehicle education and training will enable stable vehicle usage. The classification algorithm of machine learning receives the attributes (explanatory variable) of a data sample as input and classifies it as one of the categorical values of the class variable [32]. Classification algorithms belong to the supervised learning type because they provide input data along with the class values (0 or 1). A classification model is built using a training set comprising records with known class labels. The classification model predicts a class by applying the model to a set of tests with unknown class labels. In this study, we follow the process in Figure 4 to predict the driver's control transition time class based on the subjective driving questionnaire.

As presented in Table 4, we divided the reengagement time into two groups: slow and fast drivers. Similarly, in Table 6, we divided stabilization time into two groups: slow and fast drivers. We want to determine whether the reengagement time class can be classified and predicted by inputting questionnaire information into the classifier. Additionally, we want to determine whether the stabilization time class can be classified and predicted by inputting questionnaire information into the classifier. We developed a machine learning model for prediction using the k-nearest neighborhood (k-NN), support vector machine (SVM), decision tree, random forest, and logistic regression algorithms. Among the compared methods, the k-NN classifier performed best in classifying and predicting the slow and fast drivers.

Based on the data related to the 114 people comprising reengagement time class in Table 4, $Slow_{reeng}$ and

TABLE 8 Correlation between class variables and questionnaire features

Feature group	Detailed features	Correlation of reengagement	Correlation of stabilization
Demographic information	Age	0.163	0.149
	Gender	0.015[a]	−0.153
	D_Exp	−0.127	0.210
Speed driving tendency	Pleasure	0.230	−0.117
	Stress	0.190	−0.157
	Impatience	0.188	−0.035[a]
	S_Compliance	0.153	−0.170
	Flexibility	0.148	−0.174
	Accident	0.202	−0.055
	Q_Start	0.218	−0.067
	S_Increase	0.196	−0.162
Wild driving tendency	Y_Operation	0.120	−0.079
	Concession	0.048[a]	0.038[a]
	A_Interrupt	0.044[a]	−0.141
	Irritability	0.256	−0.142
	Slow_Angry	0.165	−0.060
	A_Stop	0.132	−0.071
	Rest_Area	0.124	−0.046[a]
	No_Concessions	0.060	−0.113
Driving workload weight	Mental burden	−0.160	−0.035[a]
	Physical burden	0.040[a]	−0.082
	Time burden	0.185	0.199
	Achievement	0.044[a]	−0.095
	Effort	−0.009[a]	0.109
	Frustration	0.114	0.043[a]

[a]Variables with correlation values lower than 0.05.

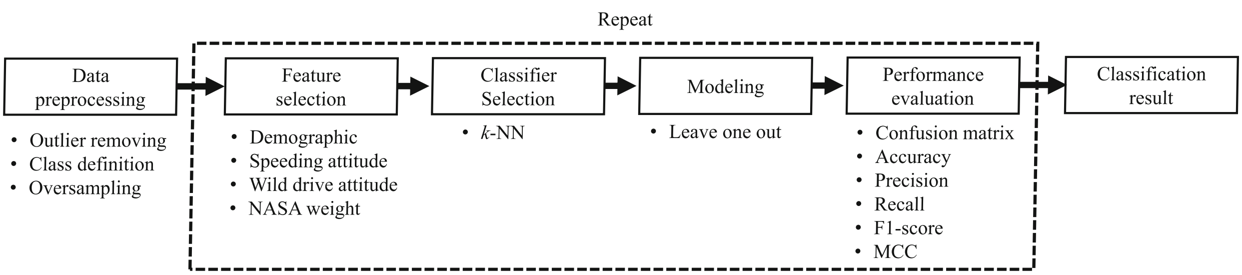

FIGURE 4 Creation and prediction process of control authority transition performance classification model

$\text{Fast}_{\text{reeng}}$ classes have 48 and 66 people, respectively; thus, there is a slight imbalance of data between the two classes. Similarly, the $\text{Slow}_{\text{stab}}$ class in Table 5 has 30 people, and the $\text{Fast}_{\text{stab}}$ class has 84 people; hence, there is an imbalance in class data. We use the leave-one-out method because the performance evaluation results are reliable when the test and training data do not overlap. Thus, a classification model is created and evaluated by separating the data from one driver as the test data and those from the remaining 113 drivers as the training data (Figure 5). This process was repeated until the data of all 114 drivers were used as the test data sample once. The performance measure was computed by averaging the prediction results of all 114 drivers.

There is a class imbalance in the training data comprising 113 drivers in the leave-one-out method (Tables 4 and 6). Besides the test with original data, we designed an oversampling approach to resolve the class imbalance. We performed oversampling on the training data, trained the classification model, and predicted the test data class label.

The k-NN algorithm is one of the pattern recognition methods based on the concept that data points of the same class should be closer in feature space. Given a training dataset of n points with the desired class specified as $\{(X_1, y_1), (X_2, y_2), \ldots, (X_n, y_n)\}$, where (X_i, y_i) represents data pair i, X_i is the feature vector and y_i is the corresponding target class. Objects are classified by the majority vote of their k-NNs. Here, k is a positive integer, which is usually a small number. If $k = 1$, then the object is assigned to the class of its nearest neighbor. It is the simplest machine learning algorithm and provides instance-based learning. The k-NN algorithm is easy to implement and debug because the process is transparent. There are noise reduction techniques that can effectively improve the classifiers' accuracy [32–35].

5.2 | Performance evaluation

In this study, we performed a leave-one-out cross-validation to evaluate the k-NN classifier. To evaluate the performance of the classification model, we used the confusion matrix in Table 9, accuracy, precision, recall, F1 score, and Matthews correlation coefficient (MCC) [32, 36]. True positive (TP) is the number of data samples predicted to be positive when belonging to the positive class. False positive (FP) is the number of data samples predicted to be positive when belonging to the negative class. True negative (TN) and false negative (FN) are defined similarly. We set the slow driver as positive and the fast driver as negative to predict a driver with slow control authority transition performance and to select it as a target for education and training.

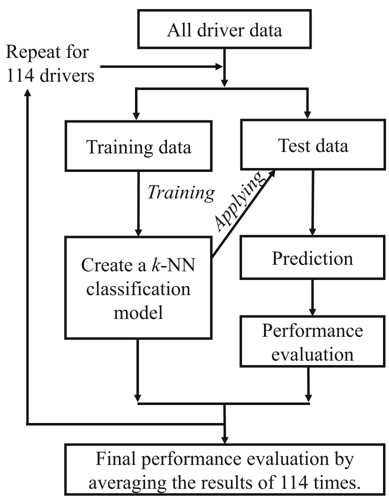

FIGURE 5 Modeling process using the leave-one-out method

Accuracy is calculated by dividing the number of correct predictions by the total number of predictions, as expressed in 1. Precision and recall are measures used in binary classification applications where the successful detection of a class is considered more significant than the detection of the other class [32].

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{FP} + \text{TN}}. \tag{1}$$

Precision is defined as the ratio of the number of samples that belong to positive classes among the samples predicted as the positive class, as expressed in 2. The higher the precision value, the better the classification model. In this study, it is the ratio of actual slow drivers to those predicted as drivers with slow reaction time.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}. \tag{2}$$

A recall is the ratio of the samples predicted to belong to the positive class among the samples belonging to the actual positive class, as expressed in 3. The higher the recall value, the better the classification model. In this study, it is the ratio predicted as a slow driver among the actual slow drivers. Recall is also called the TP rate or sensitivity.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \tag{3}$$

TABLE 9 Confusion matrix

		Predicted class	
		Positive	**Negative**
Actual class	Positive	TP (true positive)	FN (false negative)
	Negative	FP (false positive)	TN (true negative)

F1 score is the harmonic average of precision and recall, and the performance can be expressed as a single number, as expressed in 4. A high value of the F1 score ensures that precision and recall are reasonably high.

$$\text{F1 score} = 2 \times \frac{1}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}. \quad (4)$$

MCC can also be used as a performance evaluation measure of the classification model and is defined in 5 [36]. The MCC calculation method is the same as that of the Phi coefficient. MCC values from −1.0 to −0.7 and from −0.7 to −0.3 indicate strong and weak negative associations, respectively. MCC values from −0.3 to 0.3 indicate little or no association. MCC values from 0.3 to 0.7 and from 0.7 to 1.0 are judged as weak and strong positive associations [37].

$$\text{MCC} = \frac{(\text{TP} \times \text{TN}) - (\text{FP} \times \text{FN})}{\sqrt{(\text{TP}+\text{FN})(\text{TN}+\text{FP})(\text{TP}+\text{FP})(\text{TN}+\text{FN})}}. \quad (5)$$

We need to construct a classification model that detects drivers with slow control transition performance as much as possible, although it causes misclassification for fast control-switching drivers. Thus, it is necessary to determine a model with a high recall value to predict drivers with slow reengagement and those with slow stabilization as well as to educate the autonomous vehicle control transfer and manual driving stabilization so that the control authority transition can be performed quickly.

5.3 | Selection of feature variables

To verify the best feature combination for classifying the take-over transition time using subjective driving tendency information, we composed 11 feature groups by combining 25 features in the questionnaire in Table 2. The classification analysis was conducted using the *k*-NN classifier for 11 cases (Table 10).

From Cases 1 to 4, the feature group for constructing a classification consists of the features of each category in the questionnaire, such as demographic information, speed driving tendency information (Speed), wild driving tendency information (Wild), and driving workload-weighting information (NASA). From Cases 5 to 10, the features in four categories were combined in various ways. In Case 11, the features with a correlation above 0.05 in Table 8 were selected.

TABLE 10 Features used in the classification model

Case	Description of features
1	Demographics
2	Speed
3	Wild
4	NASA
5	Demographics + Speed
6	Demographics + Speed + NASA
7	Demographics + Wild
8	Demographics + Wild + NASA
9	Demographics + Speed + Wild
10	Demographics + Speed + Wild + NASA
11	Features with a correlation lower than 0.05 are removed

5.4 | Classification results

Table 11 summarizes the results of classifying slow reengagement and fast reengagement drivers as leave-one-out using the *k*-NN classifier in the original 114 data. The best performance was achieved when a training model for classification was created by extracting features based on the correlation in Case 11. The accuracy, precision, recall, and F1 score were 69%, 0.64, 0.62, and 0.63, respectively. As the MCC is 0.37, we deduced that manual driving reengagement performance can be predicted using the driving tendency questionnaires before driving a Level 3 autonomous vehicle. On the right side of Table 11, when the training model was constructed on the oversampled training data, the performance in Case 10 was the best. The classification model in Case 10 was trained using demographics, speed and wild driving tendencies, and workload weight information as features. Here, the accuracy, precision, recall, and F1 score were 71%, 0.63, 0.77, and 0.69, respectively. The MCC value was 0.43, indicating a stronger association than the performance in the left table.

Table 12 presents the results of classifying slow and fast stabilization drivers using a *k*-NN classifier. Using only the original 114 drivers' data, the best performance was achieved when the demographic information, such as age, gender, and driving experience in Case 1, was used for training. The accuracy, precision, recall, and F1 score were 77%, 0.59, 0.43, and 0.5, respectively. As the MCC is 0.36, using the demographic questionnaire, we concluded that the driver's manual driving stabilization performance could be predicted before driving a Level 3 autonomous vehicle. Performances of Cases 6, 8, and

TABLE 11 Results of classifying slow reengagement and fast reengagement drivers

			Original					After oversampling				
No.	**Case**	**Count of features**	**Accuracy**	**Precision**	**Recall**	**F1**	**MCC**	**Accuracy**	**Precision**	**Recall**	**F1**	**MCC**
1	Demographics	3	0.61	0.6	0.25	0.35	0.17	0.69	0.64	0.62	0.63	0.37
2	Speed	8	0.52	0.39	0.27	0.32	−0.04	0.60	0.52	0.67	0.58	0.21
3	Wild	8	0.56	0.48	0.48	0.48	0.10	0.59	0.51	0.62	0.56	0.18
4	NASA	6	0.58	0.50	0.44	0.47	0.12	0.54	0.47	0.58	0.52	0.10
5	D + S	11	0.64	0.59	0.48	0.53	0.25	0.65	0.57	0.71	0.63	0.31
6	D + S + N	17	0.64	0.57	0.56	0.57	0.26	0.63	0.55	0.73	0.63	0.29
7	D + W	11	0.61	0.53	0.48	0.51	0.18	0.58	0.67	0.62	0.35	0.31
8	D + W + N	17	0.61	0.53	0.50	0.52	0.18	0.68	0.60	0.69	0.64	0.35
9	D + S + W	19	0.68	0.6	0.71	0.65	0.36	0.67	0.58	0.75	0.65	0.35
10	D + S + W + N	25	0.68	0.63	0.60	0.62	0.35	0.71	0.63[a]	0.77[a]	0.69[a]	0.43[a]
11	Corr.	19	0.69	0.64	0.62	0.63	0.37	0.71	0.65	0.69	0.67	0.41

Abbreviations: Corr., correlation; D, demographics; MCC, Matthews correlation coefficient; N, NASA-TLX weight; S, speed; W, wild.
[a]Maximum performance.

TABLE 12 Results of classifying slow and fast stabilization drivers

			Original					After oversampling				
No.	**Case**	**Count of features**	**Accuracy**	**Precision**	**Recall**	**F1**	**MCC**	**Accuracy**	**Precision**	**Recall**	**F1**	**MCC**
1	Demographics	3	0.77	0.59	0.43	0.50	0.36	0.75	0.53	0.63	0.58	0.41
2	Speed	8	0.66	0.09	0.03	0.05	−0.13	0.65	0.42	0.90	0.57	0.41
3	Wild	8	0.71	0.20	0.03	0.06	−0.03	0.68	0.44	0.90	0.59	0.44
4	NASA	6	0.72	0.00	0.00	0.00	−0.08	0.61	0.35	0.57	0.44	0.18
5	D + S	11	0.71	0.40	0.20	0.27	0.12	0.69	0.46	0.93	0.62	0.48
6	D + S + N	17	0.75	0.56	0.17	0.26	0.19	0.76	0.53[a]	0.97[a]	0.68[a]	0.58[a]
7	D + W	11	0.74	0.50	0.23	0.32	0.20	0.68	0.45	0.83	0.58	0.41
8	D + W + N	17	0.72	0.44	0.23	0.30	0.16	0.76	0.53[a]	0.97[a]	0.68[a]	0.58[a]
9	D + S + W	19	0.70	0.38	0.20	0.26	0.10	0.70	0.47	0.93	0.62	0.49
10	D + S + W + N	25	0.72	0.44	0.23	0.30	0.16	0.75	0.51	0.97	0.67	0.56
11	Corr.	19	0.72	0.38	0.10	0.16	0.07	0.75	0.51[a]	1.00[a]	0.67[a]	0.58[a]

Abbreviations: Corr., correlation; D, demographics; MCC, Matthews correlation coefficient; N, NASA-TLX weight; S, speed; W, wild.
[a]Maximum performance.

11 were good when a classification model was created by composing oversampling data. Here, the measurements were between 75% and 76% accuracy, 0.51 and 0.53 precision, 0.97 and 1.0 recall, and 0.67 and 0.68 F1 scores. The MCC value was 0.58, indicating a stronger association than the performance on the left in the table.

6 | CONCLUSIONS AND FUTURE WORK

To reduce the risk of traffic accidents, several countries are installing vehicle restraint systems on roads and making significant efforts in researching core components, semiconductors, software, mapping, and automobiles necessary to prepare for the era of autonomous driving [38–43]. Many people expect autonomous vehicles to reduce the number of accidents caused by human error. Autonomous driving reduces the burden of driving. It can improve the drivers' productivity and provide them with leisure time in the vehicle. Additionally, it can reduce traffic accidents caused by manual driving and improve traffic flow efficiency. Autonomous vehicles offer the advantage of comfortable mobility in terms of sustainable mobility for the elderly and disabled.

For Level 3 autonomous driving, the driver should regain control of the vehicle whenever a TOR occurs. Thus, it is essential to switch between manual operation mode and ADS safely [1]. When the driver initiates a transfer of control to ADS, the chance of an accident is low as the autonomous driving mode is immediately activated. However, if the control authority is switched from ADS to manual driving, the response may be delayed depending on the driver's NDRT and driving efficiency. These issues in the control transition process can delay take-over time, consequently leading to an accident.

Using previously reported studies on the effect of providing driving situation information [5], providing a precue [6], using visual/auditory/tactile modality [7], and driving readiness [8,9], a method for the driver to quickly recognize TOR information and improve control transition performance was presented.

However, there have been few studies on predicting control transition performance based on the driver's characteristic and subjective tendencies and determining whether education or training is required for the driver. We used statistical analysis to examine whether driver's subjective information, such as demographics, speed and wild driving tendencies, and driving workload-weighting information, which can be obtained through questionnaires in advance, affects the control transition performance. Additionally, to verify the practical utility of subjective questionnaires information, we used the machine learning method to identify whether it was possible to classify and predict high- and low-performance drivers using only survey information before driving a Level 3 vehicle.

The statistical analysis result showed that female drivers tend to have slower control transitions than male drivers. Younger drivers physically reengaged more quickly during manual driving and had a shorter stabilization time than middle-aged drivers. Statistical analysis shows that the control transition performance varies among drivers. To determine how performance differences in control transition correlate with the subjective driving tendency information, we classified slow and fast drivers and analyzed information using prequestionnaires. After performing an independent sample *t*-test, we obtained significant differences in driving tendency questionnaire values between drivers with faster or slower reengagement time for manual driving. Similarly, there was a significant difference in the manual operation stabilization time. We conducted a correlation analysis to distinguish between slow and fast drivers based on their reengagement and stabilization time to examine if there was a correlation with the questionnaire items. The stabilization time was correlated with the gender of the driver, whereas the reengagement and stabilization time were correlated with the age and driving experience of the driver. It was observed that overspeeding and rough driving tendencies were more related to reengagement time than stabilization time. Drivers who responded that they value their time burden more when driving exhibited a good correlation with the reengagement and stabilization time performance. From the statistical analysis, the questionnaire information indicates that the drivers' subjective tendency is correlated with the drivers' manual driving reengagement and stabilization time. It is deduced that drivers' control transition performance can be predicted using the questionnaire information before driving a Level 3 vehicle.

We developed a machine learning model for prediction using *k*-NN, SVM, decision tree, random forest, and logistic regression algorithms by progressively combining demographics, speeding and wild driving tendencies, and driving workload-weighted feature information. Among the compared methods, the *k*-NN classifier performed best in classifying and predicting slow and fast drivers with respect to the reengagement and settling time than other algorithms. The classification performance with respect to reengagement time exhibited a prediction accuracy, a recall, an F1 score, and an MCC value of 71%, 0.63, 0.69, and 0.43, respectively. The performance of the stabilization time classification and prediction model was evaluated with a 75%–76% accuracy, 0.51–0.53 precision, 0.97–1.0 recall, 0.67–0.68 F1 score, and 0.58 MCC.

To prepare for commercializing Level 3 autonomous vehicles, the government should require drivers who are new to Level 3 vehicles to fill out a subjective driving tendency questionnaire to understand their driving tendencies and ability to drive vehicles safely. The results of this study can be used to establish government policies so that drivers who are new to autonomous vehicles can understand their driving tendencies through questionnaires and receive education or training on using autonomous vehicles. Additionally, autonomous vehicle manufacturers can use the results of this study to develop a personalized human–vehicle interface, which can select the method for providing driving situation information, timing of providing the precue, and method for providing the TOR according to the driver's subjective tendencies and characteristics.

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CONFLICT OF INTEREST

The authors declare no conflicts of interest.

AUTHOR CONTRIBUTIONS

Hyunsuk Kim conceived the presented idea, developed the theory, performed the machine learning analysis, and prepared the original draft. Woojin Kim, Jungsook Kim, Seun-Jun Lee, Oh-Cheon Kwon, and Cheong Hee Park verified the analytical methods. Hyunsuk Kim, Seun-Jun Lee, Oh-Cheon Kwon, and Cheong Hee Park contributed in the review and editing. Daesub Yoon performed project administration. All authors discussed the results and contributed to the final manuscript.

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