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A novel study on subjective driver readiness in terms of non-driving related tasks and take-over performance

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Abstract

This study investigates the influence of Non-Driving Related Tasks (NDRTs) on subjective driver readiness and take-over performance in level 3 automated driving system, and the effect of the readiness on driver's take-over performance. A driving simulator was used to measure driver readiness and take-over performance in the system-initiated transition situation while the driver performed different NDRTs. The results on driver readiness demonstrate that NDRT has a significant effect and the readiness influences take-over performance; driver readiness has a negative correlation with take-over time, on the contrary, a positive correlation with vehicle control quality. NDRT influenced subjective driver readiness resulting in the participants' take-over performance. We proposed a model for driver readiness and explained subjective driver readiness change at each transition phase using the analyzed data from the simulation study.

Keywords: Level 3 automated driving system; Driver readiness; Non-driving related task (NDRT); Take-over

1. Introduction

Over the last decade, a highly visible trend toward increasing automation has characterized the automotive industries. It was expected that the Automated Driving System (ADS) would reduce traffic accidents. However, safety is still one of the critical issues in conditional ADS (SAE Level 3). Following the taxonomy of the SAE [1], the level 3 system allows drivers to engage in Non-Driving Related Tasks (NDRTs) but hereby requires the driver to intervene when a Take-Over Request (TOR) occurs. Thus, the human driver should be ready to regain vehicle control during automated driving. However, taking over vehicle control can be challenging, as the task switching from NDRTs to the manual driving requires attentional resources and time-consuming reconfiguration of the driver's physical and cognitive state [2].

For the human driver to safely regain vehicle control, the driver must maintain a proper level of driver readiness before the TOR alarm. According to ISO/TR 20195-1, driver readiness has been defined as the state of a driver that influences successive driver's intervention performance to regain control of the vehicle from the system and continue driving manually [3].

Several previous studies have examined human reactions and take-over performance at the moment of system-initiated vehicle control transition. Most of these studies focused on how much time the driver needs to safely take over control and how to signal the TOR [4–7]. Kathrin et al. [5] proposed a one-dimensional take-over process model and studied driver's take-over time according to three different levels of risky driver groups. They presented a cognitive process which determined take-over performance. In a work by Yoon et al. [6], the authors found that NDRT significantly affected the take-over time and workload in a highly automated driving context.

Meanwhile, there have been few studies about driver readiness on level 3 ADS. In a work by Tina et al. [8], the authors proposed a driver readiness model for regulating the transfer from automation to human control. They presented the driver readiness ontological model and provided the knowledge base of control transfer support agents that assessed the current and predicted chauffeur state and guided the transition of control in an adaptive and personalized manner. However, they did not evaluate it using the experimental data from a simulator or actual vehicle.

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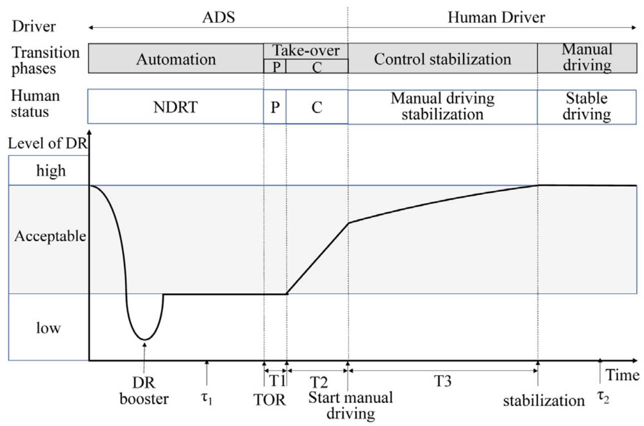

Fig. 1. The conceptual model of driver readiness in automated driving to manual driving.

The main objective of this study is to investigate the effect of NDRTs on subjective driver readiness which influences a driver's take-over performance. The driver readiness is important since it is the predictor of subsequent take-over performance. We clustered NDRTs with similar visual, auditory, cognitive, and psychomotor (VACP) demands, and then selected two NDRTs for the experimental comparison. The level 3 ADS simulator was used to evaluate subjective driver readiness and take-over performance while participants were engaged in three different tasks; two NDRTs (texting and drinking water) selected from the clusters for the experimental group and traffic environment monitoring for a comparison group. We used the NASA task load index (NASA-TLX) to measure mental workload [9]. Finally, we proposed a conceptual model for driver readiness and quantitatively explained the driver readiness change at each transition phase using the analyzed data from the simulation study.

2. Model and methods

2.1. Conceptual model of driver readiness in take-over

Fig. 1 shows the conceptual model of driver readiness and the relevant time-based metric from automation to stabilized manual driving. The transition from automated to manual can be characterized in four phases:

- ***Automation Phase***: In this phase, the ADS performs automatic driving. During the phase, driver readiness of a human driver becomes low as the level 3 ADS allows the driver to be engaged in NDRTs.
- ***Take-over Phase***: This phase covers the period and processes while the driver transitions from automated driving to manual driving. This phase starts with the TOR alarm. In this phase, the driver needs high visual, cognitive, and psychomotor resources to perceive and comprehend the TOR alarm, decide reactions, and prepare postures adequate to manual driving. This phase is considered the take-over time. The take-over time consists of T1, the time to perceive the TOR and gaze on the road, and T2, the time to understand the meaning of TOR, select an action, and prepare the psychomotor for manual driving.
- ***Control Stabilization Phase:*** In this phase, the driver initiates regaining vehicle control but requires high levels of effort to control longitudinal and lateral vehicle behavior. The phase requires control stabilization time, T3, taken until the vehicle behavior is stabilized after starting manual driving. At the end of this phase, the driver readiness reaches the level where stable control is possible.
- ***Manual Driving Phase:*** In this last phase, the driver can stably control the vehicle.

Driver readiness is a predictor of successive transition performance. Several factors influence the readiness: driver's age, manual driving skill, situational awareness, attention, position, engagement in NDRT, and confidence for ADS.

2.2. Non-driving related task clustering

NDRT Demands. According to multiple resource theory [10], people have separate attention resources and each resource has a fixed capacity, and if it exceeds capacity, it can be overloaded. Using different resources or the same resource with different coding, humans can perform tasks simultaneously with little interference. However, if humans attempt to perform two tasks simultaneously using the same resource and the same coding simultaneously, interference may occur, which can negatively affect performance. Thus, overload can occur in a single resource (VACP) or a combination of them. Therefore, an overload may occur that exceeds the capacity of the drivers' VACP resource when they are re-engaged in vehicle control while performing NDRT.

In our previous work [11], we evaluated VACP demands of 17 NDRT candidates: playing games, watching a movie, cleaning, working on the backseat, dressing up, eating, using a smartphone, computer, internet, texting, reading, conversation, listening to music, watching scenery, doing nothing, and sleeping. In this study, we found that visual demand has a statistically high correlation with cognitive demand using the evaluated VACP demands from [11] ($r = 0.65$, p-value $= 0.004^{**}$). If TOR occurs when a human driver is performing a highly visually demanding NDRT, the driver's cognitive resource is more often overloaded. As a result, the overload causes transition performance degradation and even traffic crashes. The regain of manual vehicle control requires high cognitive resources.

NDRT Clustering using K-means. We clustered 17 NDRTs into 5 groups having similar VACP demands using the evaluated VACP demands from [11]. Clustering was terminated at that sharp edge where the slope of the sum of distance is changed dramatically as depicted in Fig. 2. After clustering in five groups, the sum of distances within clusters did not decrease much. Table 1 described the clustering results.

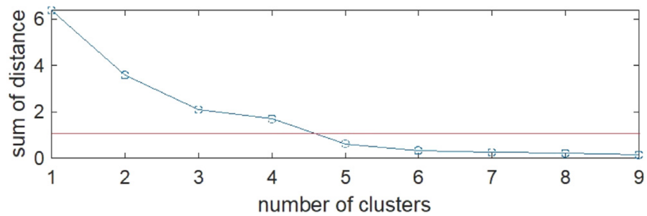

Fig. 2. Total sum of distance according to the number of clusters.

Table 1
NDRT clustering result using K-means.

Tasks	Average demand			
	Visual	Auditory	Cognition	Psychomotor
Smartphone Computer Read Internet Texting	0.87	0	0.68	0.42
Eat/drink Makeup Dress up Cleaning Backseat	0.64	0	0.16	0.77
Sleep Nothing Scenery Music	0.11	0.05	0.11	0.04
Conversation	0.14	0.70	0.76	0.00
Movie Game	1.00	0.70	0.69	0.19

Fig. 3(a) shows the clustered results of Table 1. Since the visual and cognitive demands have a high correlation, we choose only visual, auditory, and psychomotor demands as axes for 3D representation.

Hierarchical clustering. Fig. 3(b) shows the results of hierarchical clustering. The result was the same as the result using the K-mean method. The clustering was terminated when the 17 NDRTs were grouped into five clusters because the distance between clusters rapidly increased after being merged into five groups

- play games, watch movie
- conversation
- listen to music, scenery, do nothing, sleep
- work on backseat, cleaning, dress up, make up, eat/drink
- texting, use internet, read, use a computer, use a smartphone app

2.3. Experimental design and data preprocessing

Experimental Environment and Design. We constructed a level 3 automated driving simulation system to measure human reactions and driver readiness. The system is composed of a level 3 ADS simulator, a DVE monitoring server, an infra-red eye tracker, i.e., Smart Eye Pro 8.0 [12], and an ECG sensor

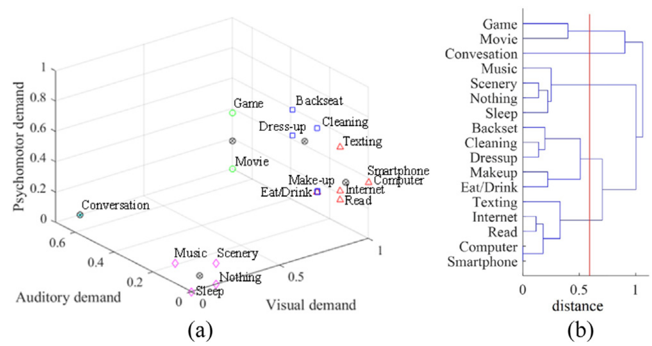

Fig. 3. (a) NDRT clustering result using K-means. (b) Hierarchical clustering result.

developed by ETRI. In this experiment, we set up the simulator to change the driving mode when the driver pressed the button to explicitly express his or her intention to change the driving mode. In the simulation scenario, the roadway was eight-lanes, two-way highway environment with four-lanes each way. The test vehicle was located in the third of the four lanes and the traffic density was low, i.e. less than 7 vehicles per kilometer and lane including vehicles in front during the entire scenario.

A total of 46 participants were recruited from the Job recruiting web site. They were aged 20–59 and required to have a valid driver's license. After the experiment was performed, the participants received $27 for their participation.

The participants were briefed on how to operate the simulator and engaged in practice driving before the experiment. During the practice driving, the participants got used to pressing the button located next to the steering wheel to change driving mode. Each participant was involved in a total of three experiments. The experiment started in the automated driving mode. During automated driving, the participants are required to be engaged in three different tasks (drinking water, texting, or monitoring traffic environments) until TOR. During drinking, we asked participants to frequently drink water while holding a water bottle in one hand. In texting task, they held a smartphone in one hand and were required to text the sentence presented by the smartphone. After two minutes of automated driving, the simulator informed the driver of the TOR alarm by an audible message "Please start manual driving". Then the participant re-engaged the vehicle control. When the driver started driving manually and got used to driving, the participant would say "Stable". After finishing each experiment, a questionnaire survey was conducted on the driver readiness, marked as 0–10 Likert scale, that the participant felt was subjective. The questionnaire also included the NASA-TLX mental workload measure.

Data Preprocessing. The data from 26 participants among 46 collected data were used for experimental data analysis. Fifteen data were removed due to failure of collecting eye tracking data. Three data were removed due to systematic errors and two data were removed due to outlier.

For transition performance analysis, we had extracted T1, T2, and T3 from the collected data. First, it was measured that

T1 as the time duration from the time of TOR alarm to the time of drivers' first gaze on the road. Second, T2 was measured the time duration between the time of the first gaze on the road and the time of pressing the driving mode button to start manual driving. Finally, T3 has measured the time duration from the time of pressing the button to the time of vehicle control fully stabilization which is similar driving pattern to their normal manual driving. To obtain normal driving data (ND), we have collected additional manual driving data after the subjects said "Stable" to the end of the experiments. It took usually 30-seconds. Then we calculated the 95% confidence interval boundary value for the mean longitudinal acceleration from the ND and denoted it by LONGSB (longitudinal stability boundary). We denoted by LATSB (lateral stability boundary) the 95% confidence interval boundary value for the mean lateral acceleration calculated from the ND. It was determined that the vehicle control had been fully stable if both the conditions (1) the longitudinal acceleration continued within the LONGSB and (2) the lateral acceleration continued within the LATSB are satisfied.

3. Results

3.1. Driver readiness measure and correlation with NDRTs

We analyzed driver readiness according to NDRTs in which the driver was engaged. The subjective driver readiness measure data were normalized to compensate for the individual participant's deviation. We found that driver readiness differed to a statistically significant degree depending on the task in which the driver participated, as shown in Fig. 4 ($F(2, 76) = 20.24$ p-value $< 0.000^{***}$). Driver readiness was the highest when a driver was engaged in DRT which involved monitoring the traffic environment (mean = 0.56, SD = 0.10). Driver readiness was degraded when the driver was engaged in NDRT rather than DRT. In particular, it was observed that Texting caused more driver readiness degradation (mean = −0.56, SD = 0.13) than Drinking (mean = 0.02, SD = 0.15). The normalized driver readiness in Fig. 4 describes the position of the driver readiness in terms of its distance from the mean. The normalized driver readiness is positive if the driver readiness during automated driving lies above the mean, and negative if it lies below the mean.

Moreover, we found that driver readiness had a statistical correlation with the task in which a driver was engaged. We propose a correlation model, Eq. (1), through regression analysis (R-square = 0.33, p-value $< 0.000^{***}$).

$$DR = 0.52 - 0.5\ \text{Drinking} - 1.02\ \text{Texting} \tag{1}$$

3.2. Transition performance measure

Drivers with high levels of driver readiness had significantly short take-over time. ($r = -0.31$, $p < 0.000^{***}$). Drivers who monitored the traffic environment had a significantly faster take-over time (mean = 2.76 s, Standard Error (SE) = 0.14) than those who were drinking (mean = 4.04 s, SE = 0.22) or texting (mean = 4.13 s, SE = 0.25) as depicted in Fig. 5(a) ($F(2,75) = 12.76$, p-value $< 0.000^{***}$). In an in-depth study about take-over time, we found significantly faster first gaze on the road, i.e. T1, when the drivers were engaged in traffic environment monitoring (mean = 0.61 s, SE = 0.25) than texting (mean = 2.13 s, SE = 0.32) ($F(2,75) = 5.89$, p-value $= 0.004^{**}$). There was no statistical difference for T2.

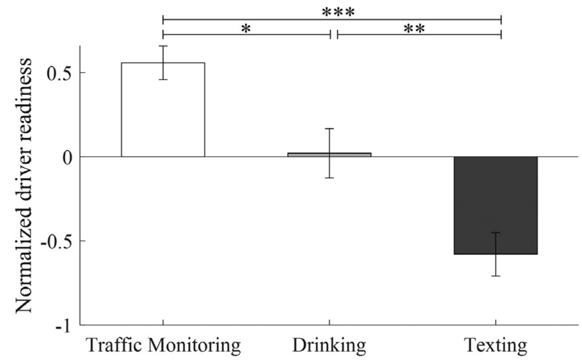

Fig. 4. Mean normalized driver readiness with standard error as error bars for each NDRT group. $n_{\text{drinking}} = 26$, $n_{\text{texting}} = 26$, $n_{\text{traffic monitoring}} = 26$ Sig. at *: P < 0.05, **: P < 0.01 ***: P < 0.001.

Fig. 5(b) shows the control stabilization time, which had no statistical difference among tasks in which the driver was engaged during automated driving ($F(2,75) = 1.12$, p-value = 0.332). It took 19.63 s (SE = 3.17) for texting drivers to stably control the vehicle after starting manual driving. It took 18.95 s (SE = 2.47) for drinking drivers and 14.47 s (SE = 2.22) for traffic monitoring drivers.

However, we found lateral vehicle control quality was significantly different during the control stabilization phase. When the driver conducted texting, standard deviation of the lateral acceleration of the vehicle was statistically higher (mean = 0.56, SE = 0.04) than when monitoring the traffic environment (mean = 0.46, SE = 0.04) ($F(2,75) = 3.91$, p-value $= 0.024^{*}$) as depicted in Fig. 5(c). In addition, the maximum lateral acceleration was significantly higher when the driver was engaged in texting (mean = 2.34, SE = 0.26), compared to traffic monitoring (mean = 1.59, SE = 0.12) ($F(2,75) = 3.46$, p-value $= 0.037^{*}$) as depicted in Fig. 5(d). Driver readiness and the maximum lateral acceleration had a negative correlation ($r = -0.28$, p-value $= 0.014^{*}$). When driver readiness was low, a driver controlled the steering wheel more dangerously. Meanwhile, we found a correlation between longitudinal vehicle control quality and driver readiness. Driver readiness had a positive correlation with minimum TTC (Time to Collision) ($r = 0.22$, p-value $= 0.048^{*}$). A driver who monitored the traffic environment tends to have longer minimum TTC (mean = 2.23 s, SE = 0.15) than a driver who was texting (mean = 1.83 s, SE = 0.16) or drinking water (mean = 1.74 s, SE = 0.15) ($F(2,75) = 2.7$, p-value = 0.07) as depicted in Fig. 5(e).

In this experiment, we found that the overall average take-over time was 3.64 s (SE = 0.14) and the control stabilization time was 17.68 s (SE = 1.53). Thus, the take-over phase and the control stabilization phase composed 27% and 83% of vehicle control transition, respectively.

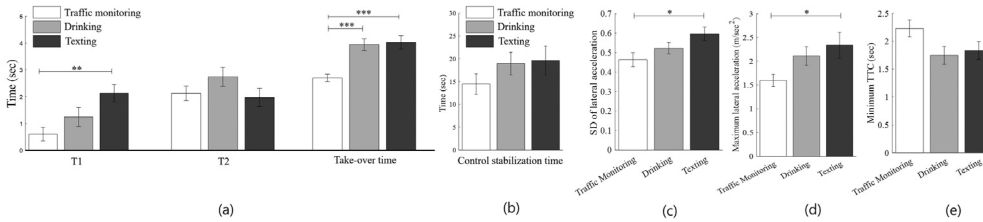

Fig. 5. (a) Mean T1, mean T2, and mean take-over time, (b) mean control stabilization time, (c) mean standard deviation of lateral acceleration, (d) mean maximum lateral acceleration, (e) mean minimum TTC with standard error as error bars for each NDRT group. $n_{\text{drinking}} = 26$, $n_{\text{texting}} = 26$, $n_{\text{traffic monitoring}} = 26$, Sig at *: P < 0.05, **: P < 0.01, ***: P < 0.001.

3.3. Mental workload measure

We found that driver readiness had a negative correlation with the mental workload measured by NASA-TLX (r = −0.30, p = 0.008**). Drivers who had high mental workload showed low levels of driver readiness. In particular, it was found that drivers who performed texting showed higher mental workloads (mean = 36.38, SE = 3.56) than drivers who monitored the traffic environment (mean = 26.15, SE = 3.33) or drunk water (mean = 26.53, SE = 3.12) (F(2,75) = 3.01, p-value = 0.05*).

4. Discussion

In Fig. 6, using the experimental results, we draw driver readiness between the time sections from τ_1 to τ_2 presented in the conceptual model in Fig. 1. When drivers monitored the traffic environment, driver readiness was at a high acceptable level during the automation phase and the P sub-phase of the Take-over phase. Then, driver readiness started to increase and reached a high level at the end of the control stabilization phase, where the driver can stably control the vehicle. The take-over time was significantly shorter because both T1 and T2 were short. The control stabilization time, T3, was also relatively short but no statistical difference with others.

Drivers engaged in the drinking water task required short T1 but long T2, so the take-over time was significantly longer than traffic monitoring. Participants acted more cautiously when putting down the water bottle than a smartphone resulting in longer body posture ready time for the manual driving. T3 was longer than T3 of traffic monitoring, but there was no statistical difference with others. During the automation phase and the P sub-phase of the take-over, driver readiness was at a moderately acceptable level. Then, driver readiness improved until reaching the high-level during the C sub-phase and the control stabilization phase. Driver readiness improvement over time was similar to that of traffic monitoring since the starting level was lower but the time taken to reach the high level was longer than those of traffic monitoring.

When drivers performed texting during automated driving, the driver needed significantly longer T1 resulting in a longer take-over than T1 of traffic monitoring. The reaction to the TOR alarm was delayed because the participants were immersed in a texting task. Some participants may consciously delay the reaction for TOR to finish the task they were doing. There was no statistically different control stabilization time, but the vehicle control quality was significantly lower than that of traffic monitoring. It was found that the longitudinal and lateral controls were degraded. Meanwhile, driver readiness was at a low acceptable level during automated driving and P sub-phase, but improved until the end of the control stabilization phase. The starting driver readiness level was significantly lower than others but the control stabilization time had no statistical difference. Therefore, driver readiness sharply increased during the improvement and showed a steep driver readiness slope.

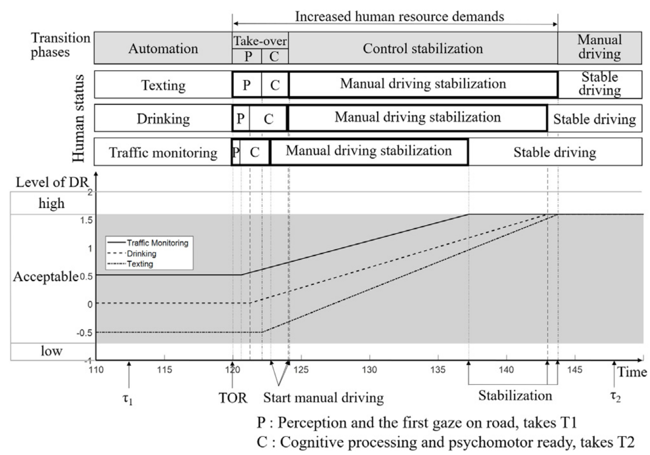

Fig. 6. Driver readiness for each NDRT during each transition phase.

The results of this study are summarized in two insights. First, visual, cognitive, and psychomotor demands affect the take-over phase of the transition. As shown in Fig. 6, drivers who performed the NDRT requiring high visual and cognitive demands like texting needed a long take-over time. Besides, drivers engaged in the NDRT requiring high psychomotor demand, like drinking water, were overloaded with psychomotor resources. Consequently, they needed longer take-over times. Second, the visual and cognitive demands of NDRT influence the control stabilization phase. When the drivers were engaged in NDRT requiring high visual and cognitive demands, driver readiness was sharply improved during the control stabilization phase. The abrupt change of the drive readiness over time requires more human resources. Indeed, it was measured that the mental workload was statistically high when a driver performs take-over while texting. It means more cognitive resources were demanded. According to the bottleneck theory, when the total demand for human resources exceeds some maximum, performance degrades. In this study, vehicle control quality has deteriorated. In particular, a cognitive resource was more easily overloaded when the driver was engaged in texting because it requires high visual and cognitive demands and they have a statistically high correlation.

Meanwhile, we cannot find driver readiness at the manual driving starting point since we did not measure it. Thus Fig. 6 is slightly different from Fig. 1. As future work, we intend to measure the difference.

5. Conclusion

In this study, we found that subjective driver readiness differed to a statistically significant degree according to NDRTs in which drivers were engaged during automated driving, and it affected the following take-over performance. Hence, it needs to measure driver readiness during automated driving and boost the readiness when necessary. We modeled and analyzed driver readiness at each transition phase according to the tasks performed by humans during automated driving. The correlation model between driver readiness and NDRTs can explain 33% of driver readiness. However, to the author's knowledge, this is the first attempt to quantitatively explain driver readiness during automated driving. Driver readiness during automation phase is important since it is the predictor of the subsequent take-over performance. Until now, most studies have focused on research during the take-over phase from TOR alarm to starting manual driving without concerning driver readiness. However, the driver readiness level influenced both the take-over and control stabilization phase. The control stabilization phase is long enough to account for 83% of vehicle control transition. Therefore, we hope that more research on the control stabilization phase will be actively conducted in the future.

CRediT authorship contribution statement

Jungsook Kim: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing - original draft. **Woojin Kim:** Methodology, Investigation. **Hyun-Suk Kim:** Investigation, Writing - review & editing. **Seung-Jun Lee:** Writing - review & editing. **Oh-Cheon Kwon:** Writing - review & editing. **Daesub Yoon:** Methodology, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.icte.2021.04.008.

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