Design and Effects of Adaptive Learning for Automated Driving Level 3

Maki Arame*
Polytechnic University, Japan
arame@uitec.ac.jp

Yoshiko Goda
Kumamoto University, Japan
ygoda@kumamoto-u.ac.jp

Junko Handa
Polytechnic University, Japan
j-handa@uitec.ac.jp

Masashi Toda
Kumamoto University, Japan
toda@cc.kumamoto-u.ac.jp

Makoto Itoh
University of Tsukuba, Japan
itoh.makoto.ge@u.tsukuba.ac.jp

Satoshi Kitazaki
National Institute of Advanced Industrial Science and Technology, Tsukuba City, Japan
satoshi-kitazaki@aist.go.jp

Automated driving level 3 has limitations of self-driving and requires a driver to drive manually when necessary. Previous research emphasizes the importance of education for automated driving. One of the biggest challenges in the safety education is the diversity of the learners from children to elders including the foreigners as transportation users. The demographics and background of the learners vary as well as their learning styles. In order to increase the acceptability and learning effectiveness of the safety education, this research aims to design the adaptive learning matching the users' career resilience and learning style to three learning contents; text, quiz, and movie. Then, the effects of adaptive learning were analyzed. The research method of the pretest and posttest quasi-experimental research was employed. Total 240 users participated into this research. The adaptive learning group and the non-adaptive learning groups were compared.

Keywords: Conditional Driving Automation, Resilience, Learning Style, Decision Tree Analysis, Logistic regression analysis.

Introduction

Research on the knowledge that drivers and pedestrians should acquire and effective education methods for advanced driver assistance systems equivalent to automated driving level 3 is an urgent issue (Zhou et al., 2019). One of the greatest challenges in safety education is the diversity of learners, from children to the elderly, including foreigners as users who face the new type of vehicles. Previous studies have confirmed individual differences in acquiring knowledge about automated driving and how to interact with automated driving vehicles (Arame et al., 2019). The objective of this study was to design an adaptive learning program that matches users' career resilience and learning styles to three learning contents in order to increase the acceptability and learning effectiveness of safety education.

Literature Review

Adaptive learning has often been discussed in the literature related to e-learning and is characterized by the optimization of learning content and learning level for each learner with ICT and social media, etc. With the advancement of ICT, various adaptive learning methods have been proposed based on the individual attributes of learners. Some adapt to their needs and preferences as well as an appropriate time for learning besides learning content and level. Generally, most of them provide appropriate learning units based on the learning level (Yamada, 2018). In this study, adaptive learning was designed to estimate learner characteristics and assign optimal learning materials.

Research Design & Methods

This study developed self-regulation learning materials for use in traffic safety courses for the general public. The materials were designed using instructional design (ID) methods, and the same content was presented in three types of media: text, video, and interactive materials. ID refers to a model or research field of methods for improving the effectiveness, efficiency, and attractiveness of educational activities, or the process of applying these methods to implement a learning environment. At first, the personal characteristics of the learners were estimated based on their career resilience (11 questions) and learning style (12 questions) scores. Based on the results, adaptive learning was constructed, in which appropriate materials were assigned from among three types of materials. Its effectiveness was verified.

Participants and Procedure

The data used in this study were an analysis of the results of 240 surveys conducted on the Internet in March 2022. Of the 240 participants, 119 were assigned adaptive learning materials suited to their individual characteristics.

In the survey, in addition to age and gender, learning styles and career resilience characteristics were surveyed as basic attributes of respondents. 20 questions about the basic knowledge of automated driving level 3 were asked the participants to answer in pre-and post-tests. The post-test provided 20 random questions administered in the pretest.

This study examined to find suitable learning materials from personal characteristic data.

Measurement

In the survey (Fig.1), learning styles and career resilience were asked to determine personality types. The questions of career resilience were used based on Kodama ("Factor 1: Challenge", "Factor 2: Diversity", "Factor 3: Future-oriented", "Factor 4: help-seeking") (Kodama, 2018). 11 questions were asked, and answers were calculated for each item from a five-point scale, from "Strongly Agree (5 points)" to "Strongly Disagree (1 point)". The sum of the mean scores for each factor was divided into three levels: less than 2.0, 2.0~3.0, and 3.0 or higher. The learning styles were based on the Felder-Silverman model, which asked 12 questions about two pairs of four areas such as Active, Reflective, Sensing, and Intuitive. The pairs of ACT-REF (1,0) and SEN-INT (1,0) were used (Felder & Silverman, 1988).

Table 1
Learning Style

category	pair	
ACT_REF	Active	Prefer discussions and explanations to others
	Reflective	Prefer to take notes, organize information and summarize important points
SEN_INT	Sensing	Prefer to learn the facts
	Intuitive	Prefer to changes

Adaptive learning was classified into 12 categories based on three levels of career resilience and four patterns of learning styles. Learning materials for each learner were assigned as a pilot test based on previous studies and the assigned learning material were shown in Table 2.

Table 2
Adaptive learning classification

	ACT-SEN (1,1)	REF-SEN (0,1)	ACT-INT (1,0)	REF-INT (0,0)
Resilience score level1	Text	Text	Text	Text
Resilience score level2	Quiz	Quiz	Movie	Movie
Resilience score level3	Movie	Quiz	Text	Quiz

Data Analyses

In this study, 20 questions about automated vehicles were asked before and after adaptive learning. The effectiveness of adaptive learning was examined in the following four ways.

1. Comparison of Prior Scores of Adaptive Learning and Non-Adaptive Learning Groups
   The data of pre-and post-scores of the adaptive learning and non-adaptive learning groups were compared. The assumption was that higher the difference between pre-and post-scores, the more effective adaptive learning was.
2. Analysis of Characteristic Factors Affecting Pre-and Post-Scores
   The data were analyzed to identify factors of characteristics affecting pre- and post-scores. The assumption was that individual characteristics that influence pre-scores would not be found in the post-scores if adaptive learning was effective. A decision tree analysis was used to find the influence of pre-post scores.
3. Analysis of Characteristic Factors using dependent variables set to 1 (up) and 0 (non-up)
   Logistic regression analysis was used to discover the factors that increased scores.
   The assumption was that individual characteristics that influence pre-scores would not be found if adaptive learning was effective.
4. Comparison of the Post-Test Scores of Adaptive Learning and Predicted Scores of Decision Tree Analysis Models
   The model created by decision tree analysis and the adaptive learning model predicted post-test scores. The assumption was that the post-scores were expected to be higher than the predicted scores if adaptive learning was effective.

Results

Results of Personal Type

Table 3 shows the number of subjects in the adaptive learning program by characteristics. There were 240 subjects, and 119 were provided with learning materials matched to their characteristics.

Table 3
Number of target persons for pattern 2

	ACT-SEN (1,1)	REF-SEN (0,1)	ACT-INT (1,0)	REF-INT (0,0)	Total
Resilience score level1	3	19	4	14	40
Resilience score level2	7	6	12	14	39
Resilience score level3	10	12	8	10	40

N=119

Data Analyses 1: Comparison of Score Increase Rate

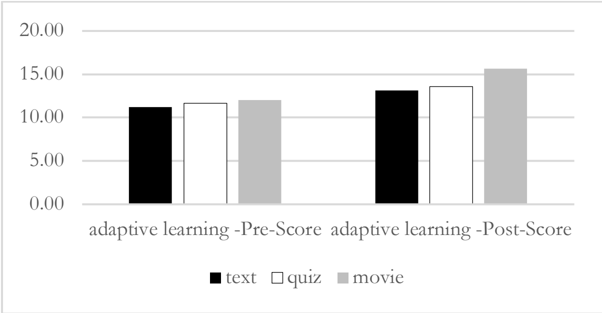
Table 4 and Figure 1 were the results of comparing the means of the pre-scores of the adaptive learning group and non-adaptive learning group, and the post-scores of the implementation group. A t-test of the means of the pre-test scores of the non-implementation group and the implementation group showed no significant difference.

Table 4
Comparison of average scores by teaching material between adaptive learning group and non-adaptive learning group in the pre-test

		Text	Quiz	Movie
Non- adaptive learning (N=121)	M	11.50	11.33	11.64
	SD	3.86	3.29	2.73
adaptive learning -Pre-Score (N=119)	M	11.19	11.65	12.05
	SD	3.45	2.82	2.86

N=240

Figure 1
Comparison of average scores between pre and post scores in the adaptive learning



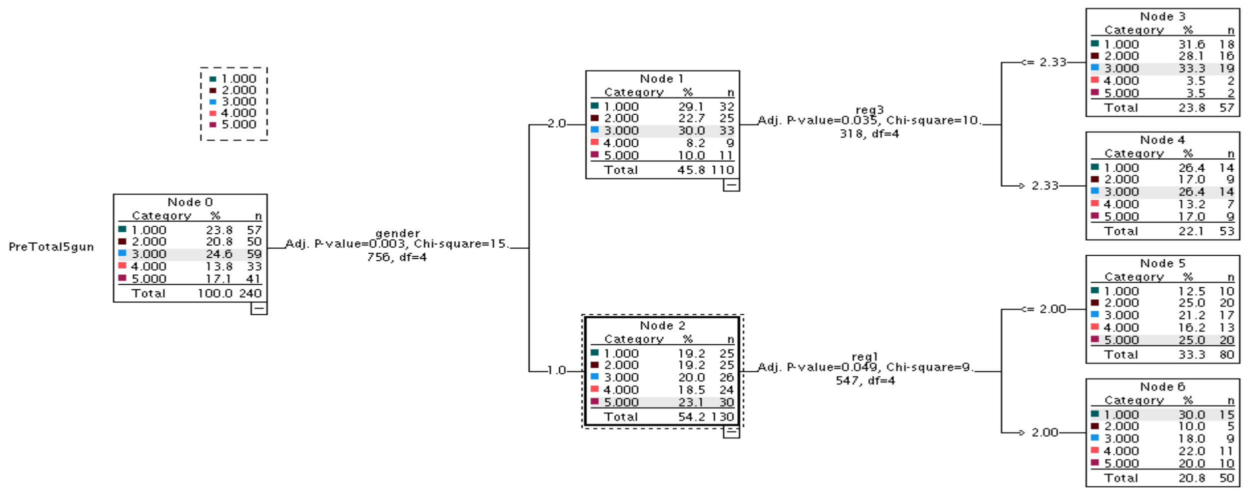
The mean difference between the pretest and posttest is 2.56 with a standard deviation of 3.57 in adaptive leaning. By learning content, the mean for text was 2.74 with a standard deviation of 3.46, the mean for quizzes was 2.74 with a standard deviation of 3.46, and the mean for videos was 3.64 with a standard deviation of 3.09. The subjects who used the movie had the highest increase in scores.

Data Analyses 2: Impact Analysis on Pre-scoring

A decision tree analysis was conducted using gender (male: 1, female: 2), age category (64 and below: 1, 64 and above: 2), resilience (L1, L2, L3), and learning style (ACT-REF (1,0) and SEN-INT (1,0)) as explanatory variables for individual characteristics on the pre-scores, and the results were shown in Figure 2. Gender had the greatest impact, and resilience level had no impact.

The assumption was that the impact of gender and resilience would not be observed in the post-test scores if adaptive learning was effective. The impact of individual characteristics on post-scores was tested with a decision tree analysis and no impact was found.

Figure 2
Result of decision tree analysis



Data Analyses 3: Impact Analysis on Post-scoring

In order to analyze the factors to increase the scores, the group whose scores increased was designated the UP group and the group whose scores did not increase was designated the non-UP group. Table 5 shows the results of the logistic regression analysis. The influence of gender was no longer observed, but there was an influence of learning style (LS_SEN_INT) and type of learning materials. The absence of gender effects after adaptive learning confirms a certain level of effectiveness but indicates that the effects of learning style and materials have not been absorbed.

Table 5
Logistic regression analysis results

	B	Sig	Exp(B)	lower limit	Upper limit

pre-scoring	-0.27	0.12	0.76	0.54	1.08
resilience	-0.25	0.44	0.78	0.42	1.46
LS_ACT_REF	-0.83	0.15	0.44	0.14	1.34
LS_SEN_INT	1.17	0.03	3.21	1.09	9.47
gender	0.44	0.35	1.55	0.62	3.85
learning contents	0.90	0.03	2.47	1.10	5.56

*p<0.05 **p< 0.01 Cox-Snell R^2 0.075 N=119

Data Analyses 4: Comparison with the predicted score of decision tree analysis

Table 6 and Figure 1 compared the adaptive learning scores with the post scores predicted by the model created by the decision tree analysis. Text and quiz scores predicted by the decision tree analysis model were higher than actual scores.

Table 6

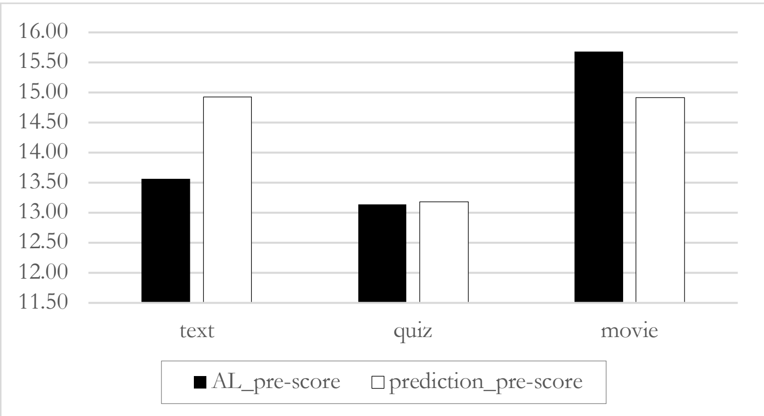
Comparison with predicted score to actual score

		text	quiz	movie
adaptive learning _pre-score	M	13.13	13.57	15.68
	SD	5.35	4.36	2.97
Prediction _pre-core	M	13.18	14.93	14.92
	SD	2.26	0.29	0.29

N=119

Figure 3

Comparison with predicted score to actual score



Discussion

This research has developed adaptive learning that assigns one of three learning contents according to individual characteristics, with the aim of dynamically allocating learning materials provided according to the characteristics of various people involved in automated vehicles. As a result of logistic regression analysis of the factors that increased the post-score, it is considered that there was effective to some degree on adaptive learning because the influence of gender disappeared. However, when the score was predicted by the model created by the decision tree analysis, the score other than the video was high in the prediction model, confirming the need for further improvement.

Two points were found in this study:

1. As a learning model for adaptive learning, the method of selecting matching learning materials from resilience and learning style has a certain effect.
2. When using the learning materials developed in this study, it is necessary to consider the influence of the learning style (LS_SEN_INT).

Combination of individual characteristics and learning materials, in short adaptive learning classification used this study may be able to absorb differences in individual characteristics. It is necessary to continue further research and improve adaptive learning.

Conclusion

In this study, adaptive learning was developed, which is a method for implementing effective learning according to individual characteristics. In the verification, a certain effect was seen in adaptive learning because the individual characteristics before the implementation were absorbed after the adaptive learning was implemented. However, the prediction of the decision tree analysis shows that the scores of the text and the quiz are higher than the scores after the actual scores. In addition, this study did pre-testing but did not consider its scoring level. Furthermore, matching was manual, not an automated system. This research is an urgent task to support the learning of diverse people. There are some limitations, but further research will be conducted.

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