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Exploring the Potential of Gamified E-Learning for Improving Heavy Vehicle Drivers' Safety Knowledge: A Feasibility Study in Ethiopia

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Abstract

Road traffic crashes remain a major global public health and economic challenge, with heavy vehicle drivers disproportionately involved in severe incidents, particularly in low- and middle-income countries. In Ethiopia, limited access to continuous professional training constrains efforts to improve drivers' safety-related knowledge and awareness. This study explored the impact potential and user acceptance of gamified e-learning modules designed to enhance heavy vehicle drivers' knowledge and awareness of fatigue management, speed-related behavior, and eco-driving practices. A randomized pretest–post-test control-group design was employed, in which professional drivers were assigned to either an intervention group that completed three gamified e-learning modules or a control group that received no training. Data were analyzed using mixed repeated-measures analysis of variance. The results revealed significant time × group interaction effects across all domains ($p < 0.001$), with substantially greater improvements in the intervention group and large effect sizes. Participants also reported high perceived usefulness, behavioral intention, and trust in the system. These findings provide preliminary evidence that gamified e-learning may be a feasible and promising approach for improving short-term safety-related knowledge among professional heavy vehicle drivers. Further research is needed to determine whether these improvements are sustained over time and translate into behavioral change and measurable road safety outcomes before broader implementation can be recommended.

Keywords: heavy vehicle drivers; e-learning; fatigue management; speeding; eco-friendly driving; Ethiopia

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1. Introduction

Road traffic safety constitutes a major global public health and socioeconomic challenge. According to the World Health Organization (WHO) Global Status Report on Road Safety, road traffic crashes remain among the leading causes of death worldwide, resulting in more than 1.19 million fatalities annually [1]. Beyond fatalities, road traffic crashes impose a substantial economic burden, with losses estimated at approximately 3% of gross domestic product in many countries [1]. These figures underscore the urgent need for effective, evidence-based interventions aimed at reducing road traffic injuries and fatalities.

Professional drivers, including heavy goods vehicle (HGV) drivers, bus operators, and delivery drivers, play a critical role in national economies by facilitating the transport of goods and passengers. However, these drivers are disproportionately exposed to occupational road safety risks. Empirical evidence indicates that HGV drivers face elevated crash risks due to factors such as fatigue, extended driving hours, and time pressure [2]. These risks generate far-reaching consequences, including loss of life, increased insurance costs, supply chain disruptions, and broader economic impacts.

Education and training are widely recognized as foundational components of effective road safety strategies. Previous studies have demonstrated that targeted training interventions can significantly reduce risky driving behaviors. For instance, reductions in excessive speeding have been reported following web-based instruction, while improvements in driver awareness have been observed through interactive training programs [3,4]. Similarly, telematics-based coaching systems significantly reduced safety-critical driving events and produced sustained behavioral improvements [5]. Despite these advancements, traditional training methods remain constrained by high costs, limited scalability, and accessibility challenges, particularly for drivers with irregular schedules [6,7].

In response to these limitations, e-learning has emerged as a flexible and scalable alternative for professional driver training. Digital platforms enable drivers to access training materials independently of time and location, making them particularly suitable for long-haul and irregular work patterns [8,9]. However, the effectiveness of e-learning depends not only on accessibility but also on user engagement. Gamification, defined as the integration of game-based elements such as feedback, rewards, and progression systems, has been shown to enhance learner motivation and engagement within digital environments [10].

In Ethiopia, road traffic safety remains a pressing concern, with fatality rates estimated at approximately 17.7 deaths per 100,000 population and heavy vehicles frequently involved in severe crashes [1]. Although regulatory frameworks mandate initial driver certification, continuous professional training remains limited due to institutional, financial, and logistical constraints [11]. This context highlights the need for innovative, scalable, and cost-effective training solutions. Gamified e-learning platforms offer a promising approach by providing flexible and engaging training tailored to professional drivers in resource-constrained environments.

Despite growing interest in digital training approaches, empirical evidence on the effectiveness of gamified e-learning for professional drivers remains limited, particularly in low- and middle-income countries. To the authors' knowledge, no randomized controlled study has evaluated both the effectiveness and user acceptance of gamified e-learning interventions among heavy vehicle drivers in Ethiopia.

Accordingly, this study aims to explore the impact potential of gamified e-learning modules on professional drivers' safety-related knowledge and awareness, including fatigue management, speed-related behavior, and eco-driving practices. In addition, the study evaluates drivers' willingness to adopt gamified e-learning as a training approach.

2. Materials and Methods

2.1. Study Design

This study adopted a randomized pretest–post-test, control-group experimental design to explore the effectiveness potential of gamified e-learning modules in improving heavy vehicle drivers' knowledge and awareness of safe driving practices (see Figure 1). The design was selected to allow for comparison of changes in outcomes over time between participants exposed to the e-learning intervention and those who did not receive any training.

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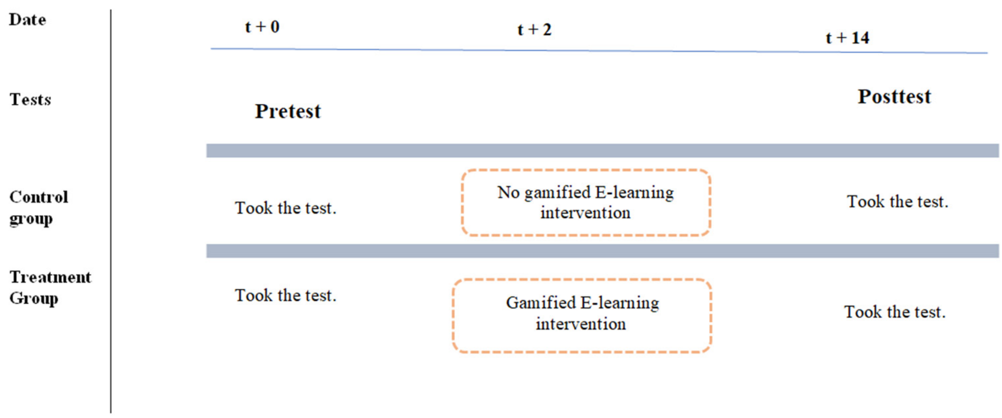

Figure 1. Schematic representation of the study design.

The study incorporated both within-subject and between-subject components. Knowledge and awareness were measured at two time points, namely prior to the intervention (pre-test) and following completion of the intervention period (post-test), constituting the within-subject factor of time. Group assignment (treatment versus control) served as the between-subject factor. This structure enabled assessment of overall changes in knowledge over time, differences between groups, and, critically, the interaction between time and group, which reflects the effect of the e-learning intervention.

Participants assigned to the treatment group completed a series of gamified e-learning modules addressing fatigue management, speed management, and eco-driving practices. Participants in the control group did not receive any form of training during the study period. By comparing pre-test and post-test outcomes across the two groups, the study design controlled for baseline differences and potential testing effects, allowing observed improvements to be attributed to the intervention.

2.2. Participants and Sampling

Participants were professional heavy vehicle drivers recruited from Misale Driving Training Academy, a licensed driver training institution located in Addis Ababa, Ethiopia. Addis Ababa was selected as Ethiopia's primary commercial and transport hub, with a high concentration of licensed heavy goods vehicle (HGV) drivers operating along major trade corridors, such as the Addis–Djibouti corridor. Misale Driving Training Academy is an officially accredited institution providing professional certification and refresher training, enabling access to actively licensed drivers within a structured training environment suitable for controlled intervention delivery. While the sample does not represent all Ethiopian HGV drivers, it reflects a formally trained segment of the professional driver population. Eligibility criteria included possession of a valid heavy vehicle driving license and active engagement in professional driving at the time of data collection. Drivers who did not complete both the pre-test and post-test assessments were excluded from the final analysis. Random assignment was conducted using an Excel-generated random allocation sequence. Eligible participants were assigned to either the intervention group or the control group in a 1:1 ratio. Formal allocation concealment procedures were not implemented because participant assignment was conducted in collaboration with the participating training institution. Eligible participants were randomly selected from a list provided by the training academy and assigned to either a treatment group or a control group. This random allocation was intended to minimize selection bias and ensure comparability between groups prior to the intervention. Figure 2 represents a CONSORT diagram giving a visual overview of the group assignment procedure.

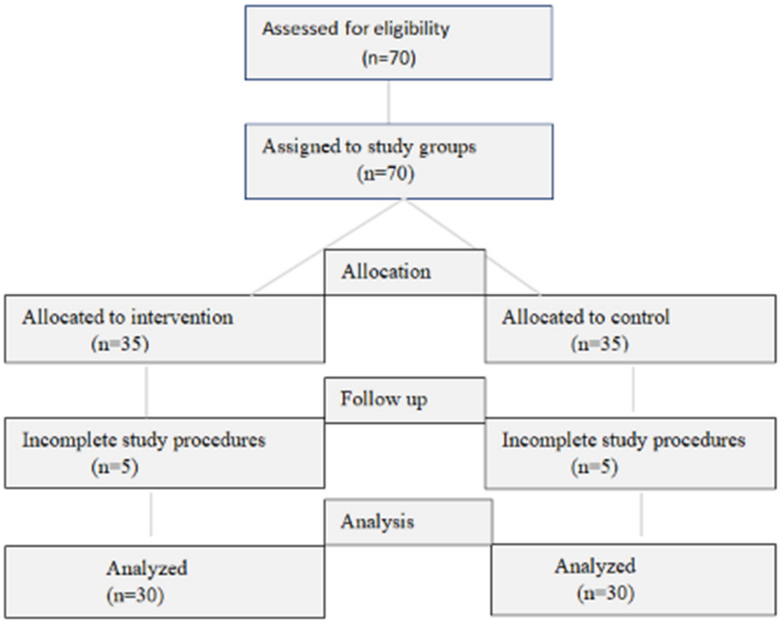

Figure 2. CONSORT flow diagram showing participant recruitment, allocation, follow-up, exclusions, and final analysis sample.

The sample size for the experimental component of this study was determined using a standard formula for comparing two independent groups in intervention research. The calculation was based on the following equation:

$$n = 2 \times [(Z_{\alpha} + Z_{\beta})/d]^2$$

where n represents the required sample size per group, Z_{α} corresponds to the critical value for a one-tailed significance level of 5% (1.645), Z_{β} represents the critical value for 80% statistical power (0.84), and d denotes the expected Cohen's d effect size. Sample size determination is a critical component of experimental design in comparative intervention studies, as appropriate power calculations help ensure the ability to detect meaningful effects [12].

In the absence of prior empirical studies reporting outcome-specific variance estimates for gamified e-learning interventions among professional heavy vehicle drivers, the expected effect size was informed by empirical evidence from related educational contexts. For example, a large effect size (Cohen's $d \approx 0.71$) has been reported when comparing game-based e-learning with conventional instruction in a randomized controlled trial [13]. Similarly, in another study, large standardized effects ($d = 0.91$–1.22) favoring e-learning over traditional teaching methods were found [14]. Although these studies were conducted in different educational domains, both involved structured digital learning interventions designed to enhance engagement, feedback processing, and knowledge acquisition mechanisms conceptually aligned with the present gamified intervention. Based on this empirical range of effects and to avoid overestimation, a conservative yet theoretically justified effect size of $d = 0.70$ was selected for the power analysis. According to conventional benchmarks for standardized mean differences, a value of $d = 0.70$ represents a medium-to-large effect [15].

Under these assumptions ($\alpha = 0.05$, one-tailed; power = 0.80; $d = 0.70$), the required minimum sample size was calculated to be 26 participants per group (total $n = 52$). The final analytical sample consisted of 30 participants per group and therefore exceeded the minimum sample size requirement derived from the power analysis described above.

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Accordingly, 70 drivers were invited to participate in the study. Following participant attrition and incomplete post-test responses, the final analytical sample consisted of 60 drivers, with 30 participants allocated to the treatment group and 30 to the control group.

2.3. Ethical Considerations

Ethical approval for this study was obtained from the Social Research Ethics Committee at Hasselt University (Approval number: REC/SMEC/VRAI/201/108; approval date: 25 January 2021). All participants were formally informed about the purpose of the study, the voluntary nature of their participation, and their right to withdraw at any time without penalty. Written informed consent was obtained from all participants before enrollment. Data were collected and stored in a manner that ensured confidentiality and anonymity.

2.4. Description of the E-Learning Intervention

The e-learning modules were designed to deliver interactive and gamified training experiences focusing on key aspects of road safety and eco-friendly driving practices. Previous studies have demonstrated that e-learning modules incorporating interactive features can enhance the effectiveness of safe driving training by increasing learner engagement and knowledge retention [16]. In particular, the integration of multimedia components such as simulations, quizzes, games, and instructional videos has been shown to significantly improve the learning process by promoting active participation and experiential learning [16]. Furthermore, research indicates that when drivers are able to interact with training content and receive immediate feedback on their performance, they are more likely to remain motivated and to adopt safer driving behaviors [17].

In the present study, the e-learning content addressed three core domains: fatigue management, safe use of speed, and fuel-efficient (eco-driving) techniques. These topics are commonly included in professional driver training programs due to their established role in reducing risky driving behaviors [4]. The selection of these domains was further informed by empirical evidence indicating that fatigue and speeding represent the primary risk factors contributing to heavy vehicle crashes in Ethiopia [18].

The course materials were developed by the Transportation Research Institute (IMOB) of Hasselt University (IMOB—https://www.uhasselt.be/en/instituten-en/transportation-research-institute-imob) using a gamified e-learning platform accessed on 18 October 2023. Gamification refers to the deliberate integration of game-design elements, mechanics, and features (like performance scores, play levels, symbolic rewards such as badges & status attributes, etc.) into non-game contexts with the objective of enhancing user motivation and engagement. Through the stimulation of intrinsic motivation, gamification facilitates the reinforcement, modification, and development of desired behaviors over time [19]. A visuall illustration of the gamified e-learning platform is presented in Figure 3.

To ensure contextual relevance, the course materials were adapted to the Ethiopian driving environment by incorporating locally relevant scenarios, terminology, and examples. For instance, the fatigue management module included references to long-haul routes commonly used by heavy vehicle drivers in Ethiopia, such as the Addis Ababa–Djibouti corridor. Similarly, the eco-driving module emphasized fuel-saving practices that reflect local fuel costs, vehicle characteristics, and prevailing road conditions.

The fatigue management module focused on increasing drivers' understanding of fatigue-related risk factors, including extended driving hours and insufficient rest. The module addressed the consequences of driving while fatigued; recognition of early warning signs of fatigue; and practical strategies for fatigue mitigation, such as appropriate rest breaks and sleep management.

The speed management module addressed speed-related risk behaviors specific to heavy vehicle operation, including speed limits, stopping distances, and the relationship between speed and crash severity. Scenario-based learning elements were used to promote risk awareness and safer decision-making.

The eco-driving module focused on environmentally sustainable and fuel-efficient driving practices, such as smooth acceleration and braking, anticipation of traffic conditions, and efficient vehicle handling. In addition to environmental benefits, the module emphasized the safety advantages of eco-driving behaviors, including improved vehicle control and reduced crash risk.

Based on the instructional design and anticipated completion time, each module required approximately one hour to complete, resulting in an estimated total instructional exposure of approximately three hours over the 14-day intervention period. In addition, participants completed pre-test and post-test assessments, each requiring approximately 20–25 min to complete.

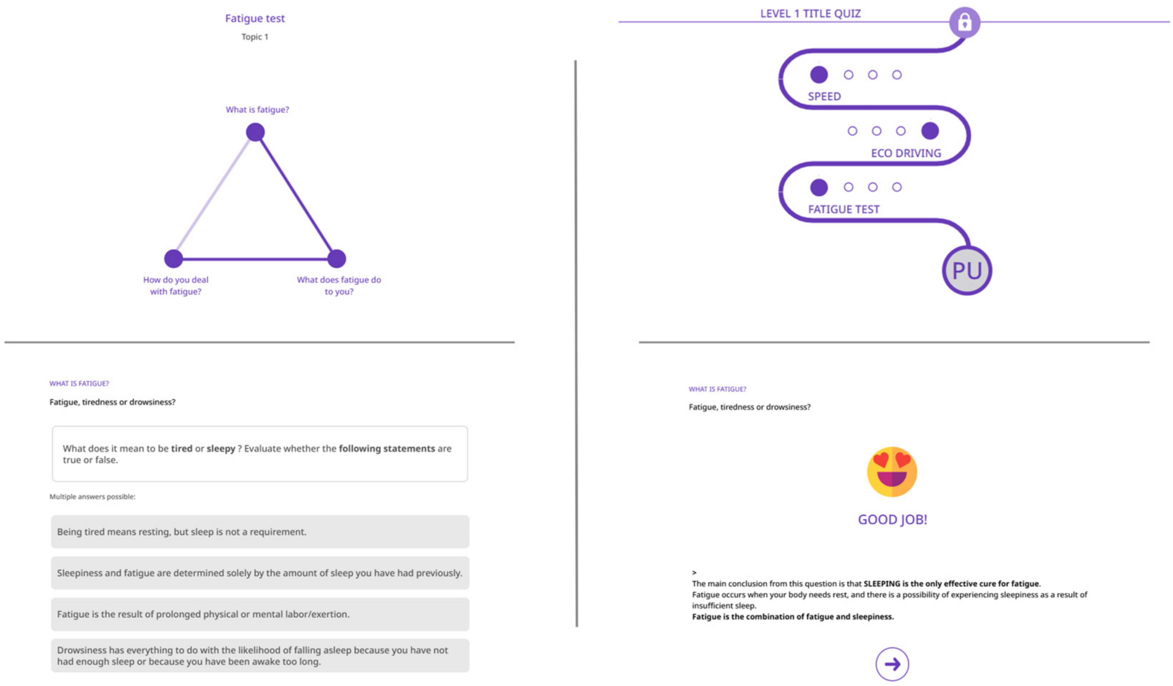

Figure 3. Visual illustration of the e-learning platform.

2.5. Measures and Instruments

2.5.1. Knowledge and Awareness Measures

In this study, knowledge refers to drivers' factual understanding of traffic regulations, risk factors, and safe driving principles, whereas awareness reflects their ability to recognize hazardous situations and appraise behavioral consequences in driving contexts. While knowledge captures declarative information, awareness relates to situational risk recognition. Similar conceptual distinctions have been observed in recent road safety research, where educational interventions were found to enhance both drivers' factual understanding and their situational recognition of unsafe behaviors and risk factors [20].

The assessment instruments were developed alongside the educational content of the intervention. To develop both the training materials and the corresponding assessment questions, we relied on several complementary sources. First, we reviewed training materials used by certified Code 95 instructors. Second, we consulted publicly available educational materials and driver training manuals from professional driver training centers. Third, we reviewed relevant scientific literature on road safety, professional driving, and behavior change, with specific attention to driver fatigue and fatigue management, eco-driving and its implementation in everyday driving, and speed-related risk behavior and strategies for maintaining safe and appropriate driving speeds. These sources were used to ensure the face validity and content relevance of both the educational questions included in the intervention and the questions used to assess intervention effectiveness.

The final selection and refinement of items were conducted collaboratively by the research team and instructors from the Misale Driving Academy. This ensured that the questions were not only theoretically grounded and evidence-informed but also contextually appropriate and relevant to the realities of professional truck driving in Ethiopia. In this way, content validity was addressed through expert review, alignment with the educational content, and contextual review by local professional driver training instructors.

All intervention and assessment materials were translated into Amharic using a back-translation protocol. Independent forward and backward translations were performed. This procedure was used to maximize conceptual equivalence across languages and cultures and to ensure that the items retained their intended meaning in the Ethiopian context, in accordance with established guidelines for cross-cultural adaptation and translation of research instruments.

As already mentioned, the outcome assessment consisted of three domains: fatigue management, eco-driving, and speed management. Each domain consisted of three subtopics, with five questions per subtopic, resulting in 15 questions per domain. The subtopics were structured around three components: what the concept means, what its consequences or relevance are, and how drivers can deal with it in practice. Questions were presented as multiple-choice or true/false items with predefined correct answers. Correct responses were scored as 1 and incorrect responses as 0. For multiple-answer questions, only the fully correct combination of answers was awarded the point. Raw scores were then transformed to a standardized 0–100 scale to facilitate comparison across the three domains. Table 1 below documents the structure of the assessment instrument. The table includes the domain, subtopic, number of items, an example question, the answer options, and the correct answer.

All knowledge and awareness assessments were administered electronically at two measurement points: prior to exposure to the e-learning intervention (pre-test) and after completion of the intervention period (post-test). The same instruments were used at both time points to ensure measurement consistency and comparability. However, because identical assessment items were administered at pre-test and post-test, potential practice or recall effects cannot be completely excluded. Higher scores indicated greater knowledge and awareness of safe and sustainable driving practices.

Table 1. The structure of the assessment instrument.

Domain	Sub-Topic	Number of Items	Example Question	Answer Options	Correct Answer(s)
Fatigue	What is fatigue?	5	What does it mean to be tired or sleepy? Evaluate which of the following statements are true.	1. Fatigue is the result of prolonged physical or mental exertion. 2. Drowsiness is related to the likelihood of falling asleep because you have not had enough sleep or because you have been awake for too long. 3. Being tired means needing rest, but sleep is not necessarily required. 4. Sleepiness and fatigue are determined solely by the amount of sleep you had previously.	Options 1, 2 & 3
	What does fatigue do to you?	5	If you drive four hours in a row, your reaction time is already seriously affected by fatigue. How much influence can fatigue have on your reaction speed?	1. Your reaction time will be, on average, 30% slower. 2. Your reaction time will be, on average, 50% slower. This doubles the chance of a crash. 3. Your reaction time will be, on average, 10% slower.	Option 2
	How do you deal with fatigue?	5	What are effective short-term countermeasures against fatigue? Multiple answers are possible.	1. Eat something while driving. 2. Stop driving and rest. 3. Open the window slightly for fresh air. 4. Take caffeine, such as coffee or an energy drink.	Options 2 & 4
Eco-driving	What is eco-driving?	5	Eco-driving and hills seem like an impossible combination. Yet it is possible. Which statements indicate how to achieve optimal fuel consumption on a hilly route? Multiple answers are possible.	1. Press the accelerator until you reach the top of the slope and also press the accelerator when descending if necessary. 2. Release the accelerator when approaching the top of the hill and when the slope flattens out. 3. When driving on long flat stretches, build momentum gradually and let it carry the vehicle uphill as much as possible.	Options 2 & 3
	What is fuel efficiency?	5	The higher a vehicle's fuel efficiency, the more distance it can travel relative to the amount of fuel it consumes.	1. True 2. False	Option 1
	How do you drive eco-efficiently?	5	After starting the engine, it is better to leave immediately and let the engine warm up gradually while driving.	1. True 2. False	Option 1
Speeding	What is speed management?	5	To properly manage your speed, you only need to pay close attention to the brake lights of the vehicle in front of you.	1. True 2. False	Option 2
	What is inappropriate speed?	5	Speed limits are targets that must be reached to ensure smooth traffic.	1. True 2. False	Option 2
	How do you manage speed under different circumstances?	5	What factors, in addition to rain, can make roads dangerously slippery? Multiple answers are possible.	1. Oil and other dirty substances can mix with water and, together with rain, can cause road surfaces to become very slippery. 2. The first drops of rain after a long dry period can make the road particularly slippery. 3. Roads become especially slippery when it rains regularly for several days, for example, in autumn.	Options 1 & 2

2.5.2. User Acceptance Measures

User acceptance of the gamified e-learning intervention was assessed among participants in the treatment group using a structured questionnaire administered after completion of the e-learning modules. The acceptance instrument was designed to capture participants' perceptions of the e-learning platform and its suitability for professional driver training.

The questionnaire measured key constructs associated with technology acceptance, including perceived usefulness, perceived ease of use, and overall satisfaction with the e-learning intervention. These constructs were informed by the Technology Acceptance Model (TAM), which identifies perceived usefulness and perceived ease of use as central determinants of users' acceptance and intention to use information systems [21,22]. The extended TAM literature further emphasizes the role of social influence and cognitive instrumental processes in shaping users' acceptance of technology-based systems [22].

Additional items assessed participants' perceptions of the relevance of the training content to their professional driving activities, as well as their willingness to engage with e-learning for future safety- and eco-driving training. Responses were recorded using a 7-point Likert-type scale ranging from 1 (strongly disagree) to 7 (strongly agree), with higher scores reflecting more positive attitudes toward the e-learning intervention.

User acceptance data were analyzed descriptively to complement the knowledge-based outcome measures and to provide insight into drivers' attitudes toward the feasibility and acceptability of gamified e-learning as a training approach in the professional driving context.

2.6. Data Collection Procedure

Data collection was conducted in two sequential phases corresponding to the pre-intervention and post-intervention measurement points. All procedures were standardized to ensure consistency across participants and study conditions.

In the first phase, eligible participants completed the baseline (pre-test) assessments prior to any exposure to the e-learning intervention. Participants completed the assessments individually under standardized conditions using a computer.

Following completion of the pre-test, participants were randomly assigned to either the treatment group or the control group. Participants in the treatment group were subsequently granted exclusive access to the gamified e-learning platform and instructed to complete all assigned modules independently online during the designated intervention period. Access credentials and usage instructions were provided. Participants were allowed to engage with the e-learning materials at their own pace during the intervention period. Participants in the control group did not receive any training or educational materials during this time.

In the second phase, after the intervention period had elapsed, all participants completed the post-test assessments using the same instruments administered at baseline. This procedure ensured direct comparability between the pre-test and post-test measurements. In addition, participants in the treatment group completed the user acceptance questionnaire following the completion of the e-learning modules. All data were collected electronically and securely stored for analysis.

2.7. Data Analysis

Statistical analyses were conducted using IBM SPSS Statistics for Windows Version 30.0 (IBM Corp., Armonk, NY, USA). Prior to inferential analysis, the dataset was screened for completeness, accuracy, and outliers. Only participants who completed both the pre-test and post-test assessments were included in the final analysis.

The primary analytical approach employed in this study was a mixed repeated-measures analysis of variance (ANOVA). This method was selected because it is appropriate for examining changes in outcome measures over time while simultaneously comparing differences between an intervention group and a control group. In the present study, time (pre-test vs. post-test) was specified as the within-subjects factor, and group (treatment vs. control) was specified as the between-subjects factor.

Separate mixed repeated-measures ANOVA models were established for each outcome domain: fatigue management, speed management, and eco-driving. For each model, three effects were evaluated: (1) the main effect of time, indicating overall changes in scores from pre-test to post-test; (2) the main effect of group, reflecting overall differences between the treatment and control groups; and (3) the time × group interaction effect, which constituted the primary effect of interest and tested whether changes over time differed between the two groups. A statistically significant interaction effect was interpreted as evidence of an intervention effect attributable to the e-learning modules.

Assumptions underlying repeated-measures ANOVA were examined prior to analysis. Because the within-subjects factor consisted of only two time points, the assumption of sphericity was inherently satisfied. Normality and homogeneity of variance were assessed using appropriate diagnostic procedures.

Effect sizes were reported using partial eta squared (${\eta^2}_p$) to quantify the magnitude of observed effects. Statistical significance was evaluated using two-tailed tests with an alpha level of 0.05 for all analyses. Estimated marginal means and 95% confidence intervals were reported to facilitate interpretation of group differences and changes over time.

In addition to the knowledge outcome analyses, descriptive statistics were used to summarize responses from the user acceptance questionnaire completed by participants in the treatment group. User acceptance outcomes were analyzed descriptively due to the exploratory nature of acceptance assessment and the absence of a comparison group.

3. Results

3.1. Participant Characteristics and Baseline Comparability

Table 2 summarizes the demographic and professional characteristics of participants in the control and intervention groups. All participants were male (100%). Overall, the two groups were comparable at baseline, with no statistically significant differences observed across demographic and professional variables (all $p > 0.05$), supporting the adequacy of the randomization procedure. The age distribution did not differ significantly between groups ($p = 0.291$). Participants aged 55–60 years were present only in the intervention group (6.67%). The mean age was 38.2 years (SD = 7.5; median = 37) in the control group and 40.5 years (SD = 8.1; median = 41) in the intervention group, with no statistically significant difference between groups ($p = 0.21$).

Educational attainment was similar across groups ($p = 0.79$). In the control group, 60% of participants had completed secondary education (grades 9–12), while 40% held a diploma or university degree. Comparable proportions were observed in the intervention group (63.33% and 36.67%, respectively). Driving experience was also comparable ($p = 0.48$), with the majority of participants reporting more than 10 years of professional driving experience (80% in the control group and 86.67% in the intervention group).

All participants reported involvement in at least one traffic crash within the past three years. Specifically, 60% of the control group and 56.67% of the intervention group reported crash involvement during this period, with no statistically significant difference between groups ($p = 0.87$). All participants indicated that their previous driver training had been delivered exclusively through face-to-face methods, and none reported prior exposure to e-learning-based training. Taken together, these findings indicate that the control and intervention groups were well matched at baseline.

Table 2. Demographic information.

	Control Group		Intervention Group		p-Value
	Frequency (N = 30)	**Percent (%)**	**Frequency (N = 30)**	**Percent (%)**	
Gender					
Male	30	100	30	100	-
Age					0.291
35–40	9	30	4	13.33	
40–45	11	36.67	12	40	
45–50	9	30	9	30	
50–55	1	3.33	3	10	
55–60	0	-	2	6.67	
Level of education					0.79
9–12 grades	18	60	19	63.33	
Degree or diploma holder	12	40	11	36.67	
Driving experience years					0.48
5–10 years	6	20	4	13.33	
More than 10 years	24	80	26	86.67	
Last-three-year traffic crashes					
Yes, once	11	36.66	11	36.67	0.87
Yes, twice	18	60	17	56.67	
Yes, three times or more	1	3.33	2	6.66	
Mode of Training					
In person	30	100	30	100	-

3.2. Assumption Testing

Prior to hypothesis testing, assumptions for mixed repeated-measures ANOVA were examined. Normality of outcome variables (eco-driving, speed behavior, and fatigue) at pre-test and post-test was assessed using the Shapiro–Wilk test. Most distributions did not significantly deviate from normality ($p > 0.05$). Given the balanced design and robustness of ANOVA to minor normality violations, all variables were retained for analysis. Mauchly's test of sphericity was not required because the within-subjects factor Time consisted of only two levels (pre-test and post-test), for which sphericity is inherently satisfied.

3.3. Effects of the E-Learning Intervention on Eco-Driving Performance

A two-way mixed repeated-measures ANOVA with Time (pre-test, post-test) as the within-subjects factor and Group (intervention, control) as the between-subjects factor revealed a significant main effect of Time (F (1, 58) = 291.41, $p < 0.001$, partial $\eta^2 = 0.834$), indicating an overall improvement in eco-driving performance from pre-test to post-test. A significant Time × Group interaction was also observed (F (1, 58) = 168.74, $p < 0.001$, partial $\eta^2 = 0.744$), demonstrating that changes over time differed significantly between groups. As shown in Table 3, eco-driving scores in the intervention group increased from 29.56 (SD = 5.50) at pre-test to 47.89 (SD = 9.07) at post-test, whereas the control group increased from 28.89 (SD = 6.32) to 31.38 (SD = 6.31). A summary of all repeated-measures ANOVA results is provided in Table 4. Bonferroni-adjusted pairwise comparisons indicated that eco-driving scores increased significantly from pre-test (M = 29.22, SE = 0.77) to post-test (M = 39.63, SE = 0.93), mean difference = 10.41, 95% CI [9.19, 11.63], $p < 0.001$. Post hoc comparisons for all outcome variables are presented in Table 5.

Table 3. Descriptive statistics for eco-driving, speed, and fatigue by group and time.

Outcome	Group	Time	*M*	*SD*	*n*
Eco-driving	Control	Pre-test	28.89	6.32	30
		Post-test	31.38	6.31	30
	Treatment	Pre-test	29.56	5.50	30
		Post-test	47.89	8.04	30
Speed	Control	Pre-test	43.03	9.58	30
		Post-test	44.27	9.10	30
	Treatment	Pre-test	44.33	9.07	30
		Post-test	79.70	14.18	30
Fatigue	Control	Pre-test	32.16	15.08	30
		Post-test	34.18	14.25	30
	Treatment	Pre-test	31.04	9.56	30
		Post-test	77.49	15.23	30

Note. M = mean; SD = standard deviation. Scores are presented on a standardized 0–100 scale, with higher scores indicating greater knowledge and awareness. Pre-test and post-test measurements were obtained before and after the intervention period, respectively.

Table 4. Results of mixed repeated-measures ANOVA for eco-driving, speed, and fatigue.

Outcome	Effect	F (1, 58)	p	Partial η^2
Eco-driving	Time	291.41	<0.001	0.834
	Time × Group	168.74	<0.001	0.744
Speed	Time	227.97	<0.001	0.797
	Time × Group	191.51	<0.001	0.768
Fatigue	Time	188.04	<0.001	0.764
	Time × Group	163.55	<0.001	0.738

Note. All effects were tested using mixed repeated-measures ANOVA with Time as the within-subjects factor and Group as the between-subjects factor.

Table 5. Bonferroni-adjusted pairwise comparisons for time effects.

Outcome	Comparison	Mean Difference	95% CI	p
Eco-driving	Pre vs. Post	10.41	[9.19, 11.63]	<0.001
Speed	Pre vs. Post	18.30	[15.63, 20.97]	<0.001
Fatigue	Pre vs. Post	24.23	[21.02, 27.44]	<0.001

Note. Pairwise comparisons are based on estimated marginal means with Bonferroni adjustment.

3.4. Effects of the E-Learning Intervention on Speed Behavior

For speed behavior, the mixed repeated-measures ANOVA revealed a significant main effect of Time (F (1, 58) = 227.97, $p < 0.001$, partial $\eta^2 = 0.797$). The Time × Group interaction was also statistically significant (F (1, 58) = 191.51, $p < 0.001$, partial $\eta^2 = 0.768$), indicating differential changes between the intervention and control groups. Post hoc Bonferroni-adjusted comparisons showed a significant increase in speed-related scores from pre-test (M = 43.68, SE = 1.21) to post-test (M = 61.98, SE = 1.54), mean difference = 18.30, 95% CI [15.63, 20.97], $p < 0.001$. Improvements were significantly greater among participants who completed the e-learning modules.

3.5. Effects of the E-Learning Intervention on Fatigue Management

Analysis of fatigue scores demonstrated a significant main effect of Time (F (1, 58) = 188.04, $p < 0.001$, partial $\eta^2 = 0.764$). A significant Time × Group interaction was also observed (F (1, 58) = 163.55, $p < 0.001$, partial $\eta^2 = 0.738$), indicating that fatigue-related knowledge changes differed significantly between groups. Bonferroni-adjusted pairwise comparisons revealed a significant increase in fatigue scores from pre-test (M = 31.60, SE = 1.63) to post-test (M = 55.83, SE = 1.90), mean difference = 24.23, 95% CI [21.02, 27.44], $p < 0.001$. The intervention group exhibited significantly larger gains compared with the control group.

3.6. User Acceptance of the E-Learning Modules

User acceptance indicators demonstrated a strong positive evaluation of the gamified e-learning platform among participants in the treatment group (n = 30). Overall attitudes were favorable, with 80% of drivers reporting positive perceptions of the modules. Behavioral intention to adopt the approach was unanimous, as all participants (100%) indicated willingness to use similar digital training in the future.

Perceived behavioral control was likewise high, with all respondents (100%) expressing confidence in their ability to use the e-learning system effectively. Perceived usefulness was strongly endorsed: 90% of participants agreed that the modules would enhance driving safety, and 100% reported that the intervention could improve the effectiveness of their driving-related activities.

Perceptions of ease of use were more moderate, with 60% of participants agreeing that the modules were easy to use. Subjective norms were positively endorsed by 70% of respondents, indicating perceived social support for adoption. Trust in the platform was uniformly strong, with all participants (100%) expressing confidence in its potential to improve driving performance.

4. Discussion

4.1. Impact Potential of Gamified E-Learning for Driver Safety Training

This study examined the impact potential and acceptance of gamified e-learning modules designed to improve heavy vehicle drivers' knowledge and awareness of fatigue management, speed management, and eco-driving practices in Ethiopia. Using a randomized pretest–post-test control-group design and mixed repeated-measures ANOVA, the findings provide first exploratory evidence that drivers who participated in the e-learning intervention achieved significantly greater improvements across all learning domains compared to those in the control group. The consistently significant Time × Group interaction effects, accompanied by large effect sizes, strongly suggest that the observed knowledge gains can be attributed to the intervention rather than to general learning or testing effects.

Although the Time × Group interaction effects were large across all three outcome domains, these effect sizes should be interpreted within the context of the baseline knowledge levels observed in the study population. Participants demonstrated relatively low pre-intervention scores in several domains, particularly eco-driving and fatigue management, indicating substantial scope for improvement. A plausible explanation for these lower baseline scores is that the assessment focused on specialized knowledge areas, including fatigue management, eco-driving, and speed management, which may not be routinely emphasized in professional practice or refresher training programs. Although all participants were licensed heavy vehicle drivers, prior exposure to these specific concepts may have varied considerably across individuals. Furthermore, the assessment instruments were designed to evaluate domain-specific knowledge closely aligned with the intervention content rather than general driving competence. Consequently, the relatively low pre-intervention scores may reflect limited familiarity with these specialized topics rather than inadequate overall professional driving knowledge or experience. Therefore, the large effect sizes should be interpreted as indications of strong short-term learning gains within the present study context rather than definitive evidence of long-term or broadly generalizable intervention effects.

The pronounced improvements observed in fatigue management and speed-related knowledge are particularly important given the well-established role of these factors in heavy vehicle crashes. Previous studies have identified driver fatigue and speeding as key contributors to crash risk and severity, particularly among professional drivers operating under conditions of extended driving hours and time pressure [11,18]. By directly targeting these high-risk behavioral domains, the intervention addressed core safety challenges within the professional driving context, which likely contributed to the magnitude of the observed learning gains.

Improvements in eco-driving knowledge further highlight the broader applicability of gamified e-learning beyond immediate safety outcomes. Eco-driving practices have been shown to improve fuel efficiency, reduce emissions, and enhance overall driving smoothness, particularly when supported by structured feedback and performance-based learning systems [23]. However, our results also show a lower absolute gain in eco-driving knowledge when compared to speeding and fatigue. Although not investigated as part of this study, we hypothesize that this likely reflects the greater conceptual complexity and multi-dimensionality of this domain relative to speed and fatigue. Eco-driving integrates fuel efficiency, environmental awareness, and vehicle handling techniques, areas where baseline knowledge among professional heavy vehicle drivers in Ethiopia may be lower and where concepts are less immediately familiar than regulatory speed limits or fatigue recognition. Additionally, the post-test mean score of 47.89/100 suggests that participants had not yet achieved maximal performance in this domain, indicating potential for further improvement with additional training or repeated exposure. The comparable interaction effect sizes indicate that gamified e-learning was equally effective as an intervention across all three domains, even if the starting points and achievable ceilings differ. The present findings demonstrate that such multidimensional training content can be effectively delivered through digital learning platforms, thereby extending the benefits of e-learning to both safety and environmental domains.

The impact potential of the intervention may be partly explained by the integration of gamification elements within the e-learning modules. Gamification has been widely recognized as a strategy for increasing learner engagement, motivation, and persistence by embedding game-like elements within instructional environments [10]. In professional training contexts, gamified approaches have been shown to enhance attention and facilitate deeper learning when aligned with clearly defined instructional objectives [10]. In the present study, the incorporation of quizzes, interactive scenarios, and immediate feedback likely supported active learning processes and reinforced key safety messages. These findings are consistent with prior research emphasizing the importance of interactivity and feedback in driver education and behavior change [24].

Although the findings provide the first exploratory indications of the impact potential of the intervention, the present study was not designed to isolate the independent contribution of gamification features. Participants in the intervention group received structured educational content, interactive learning activities, and enhanced engagement opportunities that were not available to the control group. Consequently, the observed improvements should be interpreted as the result of the intervention package as a whole rather than definitive evidence of the unique effectiveness of gamification alone.

In addition, the study revealed high levels of user acceptance of the gamified e-learning approach. Participants reported strong perceived usefulness, positive attitudes toward the platform, and a high intention to use similar systems in the future. These findings align with the Technology Acceptance Model, which identifies perceived usefulness and ease of use as key determinants of technology adoption [25]. Previous research further suggests that interactivity, perceived relevance, and user experience play critical roles in shaping acceptance of digital learning systems [17,26]. The strong acceptance observed in this study indicates that gamified e-learning is practically viable within the professional driver training environment.

This feasibility study makes an important contribution to the literature by providing experimental evidence from a low- and middle-income country context, where empirical research on digital driver training remains limited. By integrating both impact potential and user acceptance within a randomized controlled framework, the study extends current knowledge on the applicability of gamified e-learning in professional driver training, particularly in resource-constrained settings.

4.2. Practical and Policy Implications

The findings of this study provide important implications for professional driver training and road safety education in Ethiopia. The demonstrated improvements in short-term safety-related knowledge and awareness suggest that gamified e-learning may serve as a useful complementary tool within driver training systems. However, because the study did not assess real-world driving behavior, traffic violations, crash outcomes, or long-term retention, the findings should not be interpreted as direct evidence of improved road safety performance. Rather, they indicate that gamified digital training represents a promising educational approach that warrants further evaluation before large-scale regulatory integration.

Given the logistical constraints associated with traditional face-to-face training, including travel requirements, instructor availability, and operational downtime for commercial drivers, digitally delivered modules offer a practical and scalable solution. Such approaches can reduce participation barriers while maintaining standardized instructional quality, making them particularly suitable for professional drivers with irregular schedules [27].

Second, the strong user acceptance observed among professional drivers suggests that the integration of digital safety modules into license renewal processes may be operationally feasible. Evidence from Ethiopia indicates that drivers perceive e-learning as flexible and relevant, particularly when supported by interactive and context-specific content [28]. Similar patterns of acceptance have been observed in studies examining technology-mediated safety interventions, where drivers reported high levels of perceived usefulness, trust, and willingness to adopt digital systems [29]. These converging findings support the feasibility of embedding gamified e-learning within formal regulatory and training frameworks.

Transport authorities may consider piloting certified digital training modules within existing professional driver training, license renewal, or continuing education programs. Such an approach would institutionalize continuous driver training while minimizing administrative and logistical burdens. Evidence from digital road safety education indicates that structured online training integrated into regulatory systems can improve risk awareness and sustain long-term engagement with safe driving practices [29,30].

At the organizational level, fleet operators and transport companies may benefit from integrating gamified digital training into internal safety management systems. Research suggests that interactive e-learning aligns with operational safety priorities and can enhance driver performance and safety-related competencies [28,31]. Such integration may contribute to improved compliance, reduced safety incidents, and enhanced overall fleet performance.

Furthermore, the modular structure of gamified digital content enables adaptation to regional risk conditions, language requirements, and evolving regulatory frameworks. In rapidly motorizing contexts such as Ethiopia, scalable digital training solutions provide a mechanism for delivering consistent safety education across geographically dispersed driver populations [32].

Finally, from a cost-efficiency perspective, digital training offers significant advantages by reducing recurring expenses associated with instructor-led sessions and physical training facilities. Although initial investment in digital infrastructure is required, the marginal cost per additional trainee is substantially lower compared to traditional approaches. This cost structure is particularly relevant in low- and middle-income countries, where road safety resources are constrained, but the burden of heavy vehicle crashes remains high [33,34].

4.3. Limitations and Future Research

Despite its contributions, this study has several limitations that warrant careful consideration. First, the sample size was relatively modest, and participants were recruited from a single licensed heavy vehicle driver training institution in Addis Ababa. In addition, all participants were male. Although this composition reflects the demographic characteristics of the professional heavy vehicle driver population available within the study setting, it limits the generalizability of the findings. The study was designed primarily to evaluate intervention impact potential under controlled conditions rather than to generate nationally representative estimates. Consequently, the findings should be interpreted as evidence from a formally trained group of professional heavy vehicle drivers and may not fully represent drivers from other regions or training contexts. In addition, the study population was drawn from a licensed training institution and therefore reflects a specific segment of the professional driving workforce. The findings may not generalize to informal-sector heavy vehicle drivers who operate outside formal training and employment structures. Future research should evaluate the intervention across multiple institutions, geographic regions, and more diverse driver populations to strengthen external validity.

Second, this was a feasibility study that evaluated short-term knowledge acquisition rather than long-term behavioral change or objective safety outcomes. In addition, outcomes were assessed immediately following completion of the intervention, and no delayed follow-up assessment was conducted. Consequently, the persistence of the observed knowledge and awareness gains over time remains unknown. Knowledge acquired through training interventions may decline if not reinforced through continued practice or refresher training. Therefore, the present findings should be interpreted as evidence of short-term learning gains rather than long-term knowledge retention, behavioral adaptation, or measurable safety improvements. Future research should incorporate longitudinal follow-up assessments and objective behavioral indicators, such as telematics-based driving measures, traffic violations, and crash involvement, to evaluate the sustainability and real-world impact of the intervention.

The third limitation relates to the potential for contamination between study groups. Participants in both the intervention and control groups were recruited from the same training institution and may have interacted during the intervention period. Although only participants in the intervention group were granted access to the e-learning modules, informal communication regarding training content cannot be completely ruled out. If such information exchange occurred, it would likely have reduced differences between groups and resulted in a more conservative estimate of the intervention effect. Future studies

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should consider additional measures to minimize potential contamination, including cluster randomization, institutional separation, or monitoring of participant interactions.

A fourth limitation relates to the use of a no-training control group rather than an active comparison condition. As a result, the observed improvements may partly reflect increased engagement, novelty effects, structured learning exposure, or other intervention-related influences in addition to the gamification features themselves. Consequently, the findings suggest that the intervention improved short-term knowledge and awareness compared with no training. However, they do not establish whether gamified e-learning is superior to conventional face-to-face training, non-gamified e-learning, or other structured educational approaches. Previous research has emphasized the importance of active comparison groups when evaluating the specific contribution of gamification to learning outcomes and learner engagement [35]. Future studies should therefore incorporate active control conditions to isolate the specific contribution of gamification beyond the effects of instructional content, attention, and learning exposure.

Fifth, although the knowledge assessment and user acceptance instruments were developed based on the intervention content and relevant literature, they did not undergo a comprehensive psychometric validation process. Consequently, additional evidence regarding construct validity, measurement properties, and reliability would strengthen confidence in the assessment tools. Future research should formally evaluate the psychometric properties of these instruments using established validation procedures and larger samples.

Sixth, user acceptance measures were based exclusively on self-reported perceptions of usefulness, satisfaction, trust, and behavioral intention collected from participants in the intervention group. Although such constructs are well-established predictors of technology adoption, they remain susceptible to social desirability bias, instructor-related response effects, and perceived expectations associated with structured training environments. The particularly high levels of reported trust and intention to use the platform should therefore be interpreted cautiously, as they may not necessarily translate into actual long-term adoption or sustained engagement. Future studies should incorporate anonymous assessments, qualitative interviews, objective usage analytics, and longitudinal follow-up measures to provide a more comprehensive evaluation of user acceptance and technology adoption.

Future research should therefore extend evaluation beyond immediate post-intervention knowledge gains. Longitudinal designs incorporating behavioral indicators such as telematics-derived speeding patterns, fatigue-related driving metrics, fuel consumption records, and officially recorded traffic violations or crash involvement would allow for a more comprehensive assessment of real-world safety impact. Larger, multi-site studies involving diverse driver populations would enhance statistical power and strengthen generalizability across organizational and regional contexts. Additionally, experimental comparisons between gamified and non-gamified digital formats could isolate the specific contribution of motivational design elements to learning outcomes.

5. Conclusions

This study explored the impact potential of gamified e-learning modules in improving heavy vehicle drivers' knowledge and awareness of fatigue management, speed management, and eco-driving practices in Ethiopia. Using a randomized pretest–post-test control-group design and repeated-measures analysis, the findings demonstrated that drivers who participated in the e-learning intervention achieved significantly greater improvements across all three learning domains compared to those who received no training.

The results provide preliminary empirical evidence that the intervention may offer a promising educational approach for professional driver training, particularly in resource-constrained contexts where access to continuous professional development opportunities may be limited. However, further research involving larger and more diverse driver populations and longer follow-up periods is required before conclusions regarding scalability and broader applicability can be drawn. The substantial improvements observed among participants in the intervention group suggest that interactive and feedback-oriented digital learning can effectively enhance short-term safety-related knowledge and awareness. These findings suggest that digitally delivered training may serve as a useful complementary component of professional driver education programs, although further research is required to establish its longer-term effectiveness and broader applicability.

In addition to learning outcomes, participants' positive acceptance of the e-learning approach indicates a strong readiness among professional drivers to engage with digital training tools. High levels of perceived usefulness, behavioral intention, and trust in the system highlight the acceptability of the intervention among study participants. While some usability challenges were noted, these do not undermine the overall acceptability of the intervention within the context of this feasibility study.

From a practical perspective, the findings suggest that gamified e-learning modules may complement existing driver training and road safety education initiatives targeting heavy vehicle operators. However, large-scale policy integration should be preceded by further research using longitudinal designs and objective behavioral indicators, including telematics data, traffic violation records, fuel-consumption measures, and crash-related outcomes. Such evidence is necessary to determine whether short-term knowledge gains translate into sustained behavioral change and measurable road safety benefits.

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