Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 963 – 976
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5901

Implementation of Driver Behaviors Risk Detection and Safety Alert System in Road Transport Management: A Case Study of Nong Khai Border Checkpoint

Varangkoon Issaragura Na Ayuthaya[1], and Metinee Rasadaraksa[2]

Abstract

This research analyzes the management framework for transnational commercial transport at the Nong Khai border checkpoint. This research aims to create an AI prototype for a cross-border commercial transportation management system by integrating a driver behavior risk identification and safety alert system. This study is a survey investigation that gathers data through a questionnaire. The sample population comprises 400 cross-border transportation operators. The data were examined utilizing descriptive statistics, frequency distribution with percentages, arithmetic mean, standard deviation, and inferential statistics. The technique employs confirmatory factor analysis (CFA) and structural equation modeling (SEM) to assess the alignment of the research model with empirical data (model fit). The model demonstrated consistency with the actual data, evidenced by a Chi-Square value of 70.920, degrees of freedom (df) of 57, significance (Sig.) of 0.102 (more than 0.05), and a CMIN/df ratio of 8.864 (less than 5.0). The analytical findings from the model adjustment indicated that seven indices were consistent, and these statistical values met the necessary criteria. This prototype Module system is designed to assess the effectiveness of cross-border freight services provided by Thai logistics operators and to enhance safety standards and the possibility for effective cross-border transport management between Thailand and Lao PDR.

Keywords: *Accident Reduction, Truck Drivers, The Factors Causing the Accident, Driver Monitoring System.*

Introduction

Cross-border commerce between Thailand and Laos has been steadily increasing. Thailand shares a boundary with Laos, delineated by the Chong River. There are twelve provinces next to the boundary. The northeastern region comprises six provinces next to the Mekong River: Loei, Nong Khai, Ubon Ratchathani, Nakhon Phanom, Mukdahan, and Amnat Charoen. Four Thai-Laos Friendship Bridges exist in Nong Khai, Mukdahan, Nakhon Phanom, and Chiang Rai. Nevertheless, when evaluating the logistics sector, infrastructure advancement, and efficient transportation pathways, Nong Khai Province serves as the economic centre of the region, aligned with the North Southern Economic Corridor (NSEC) and the Eastern Economic Corridor (EEC) within the Greater Mekong Sub-region (GMS) economic cooperation framework. The infrastructure and logistical systems of the aforementioned border provinces provide the potential for the advancement of several dimensions, including economic, social, cultural, and national security.

Based on an analysis of previous research documents, including numerous articles on border trade and community economy, the researcher was prompted to evaluate the potential of Nong Khai border province due to the encouragement of investment and technology transfer aimed at improving the competitiveness of the member countries. Nong Khai province possesses significant infrastructure for transportation and logistics systems that facilitate the enhancement of border trade (Kaewmanee, 2012). Although the economic system as a whole has expanded, traffic accidents have persistently increased. The 2020 worldwide road safety report aligns with numbers from Thailand, revealing that truck-related fatalities rose from 636 in 2017 to 1,148 in 2018, with a continuing upward trend annually. In 2019, Nakhon Ratchasima Province recorded the highest number of truck-related road accidents in the Northeast along the Bangkok to Nong Khai cross-border trade route. In 2018, it held the second position in this category. Consequently, Thailand is confronting an escalating issue of road safety. Various agencies have attempted to address this

[1] Faculty of Business Administration, Rajamangala University of Technology Thanyaburi, Thailand, Email: varangkoon_i@rmutt.ac.th

[2] Faculty of Business Administration, Rajamangala University of Technology Thanyaburi, Thailand, Email: metinee_r@rmutt.ac.th, (Corresponding author)

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 963 – 976
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5901

concern by proposing measures to mitigate accident rates. The Department of Land Transport intends to mandate the installation of GPS tracking systems and driver identification devices in public buses and large trucks as a preventive strategy to enhance safety and diminish risk factors associated with road accidents. This initiative also aims to regulate and monitor road usage behaviors, enforce speed limits, and manage driving hours to facilitate vehicle movement oversight.

This research will create a prototype AI system for managing cross-border freight transport by implementing a risk detection system based on driver behaviors and providing safety alerts within the cross-border trade transport management system. The aim is to examine the factors influencing truck driver accidents—case Study: Nong Khai Border Checkpoint. The researcher will examine two components as outlined below: **Part 1:** Creation of a Risk Behaviors Detection System, The Red Alert Drowsiness System is an additional mechanism designed to notify drivers experiencing drowsiness or facing hazardous conditions to avert accidents. The initiative aims to preserve lives and prevent disasters and losses affecting persons and organization's lives and properties. The program will be built for the Android operating system to monitor and promptly alert when hazardous behaviors are identified. It can analyze driving by utilizing data from sensors, specifically those on the user's smartphone, to gather information on vehicle operation. **Part 2:** Data collection from a sample of 400 truck drivers traveling from Bangkok to the Nong Khai border post via the Simple Random Sampling technique. The data collection instruments included a general information questionnaire addressing factors contributing to accidents and a questionnaire focused on accident mitigation for truck drivers. The data were analyzed utilizing descriptive statistics, including counts, percentages, averages, standard deviations, Independent-Samples T-Test, One-Way ANOVA, and Correlation Coefficient Analysis.

Literature Reviews

Global Positioning System Vehicle Tracking System

Real-time tracking enables the monitoring of cars, ensures drivers adhere to the safest or predetermined routes, and provides comprehensive visibility and control over your fleet. Minimize vehicle running expenses, enhance efficiency, and expand your enterprise. Obtain the precise GPS coordinates of your vehicles in real time. Utilized Driver ID tags to identify the operator and modify Satellite views or Smart-Map Overlays according to your requirements.

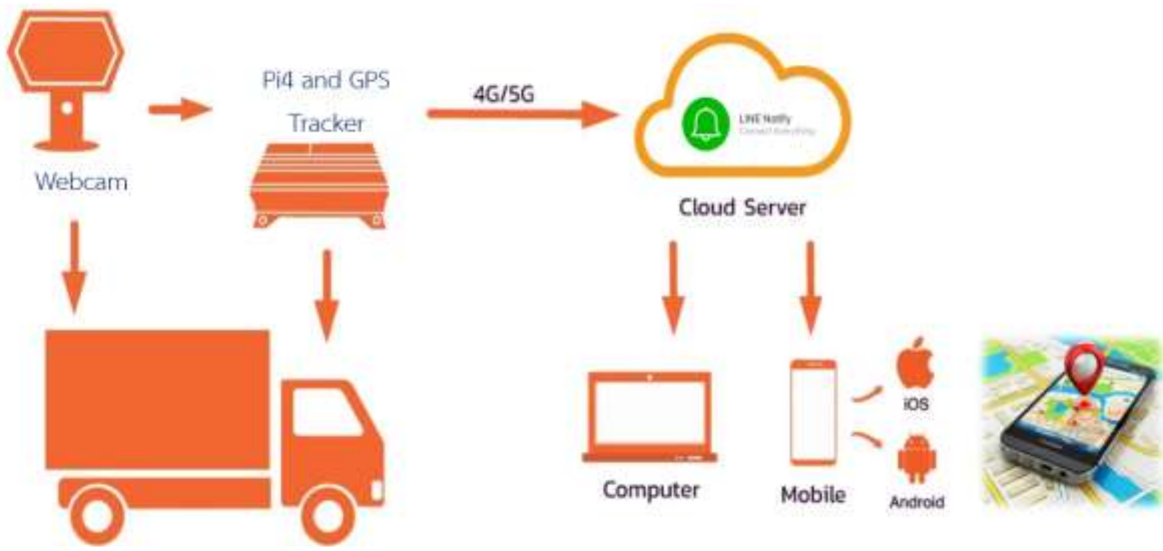

Fig 1. Global Positioning System Vehicle Tracking System

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 963 – 976
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5901

Table 1. Review Of Literature on GPS Vehicle Tracking Devices

Researcher's name	Title	Instruments utilized in research	Procedure
Doremoni Mallesh Kumar et al., (2016)	School Children Transportation and Safety Enhancement System Based on RFID	Implemental and Experiments	Design of transportation safety system for school children based on RFID technology
Khaled Shaaban et al.,(2013)	Investigating the Customer Satisfactions of the Bus Service in Qatar	Questionnaire	Utilized a questionnaire to get data on risks and satisfaction levels.
Saniah Ahmed et al.,(2015)	Between Tourism and Intangible Cultural Heritage	Questionnaire	Utilized questionnaires to get intangible risk information.
Vishaka Asundkar et al.,(2016)	Guidelines Against Sexual Harassment at Workplace	Questionnaire	Study monitoring methods to improve the safety of tracking systems for educational institutions and minors.

Driver Monitoring System (DMS)

DMS is a device designed to enhance road safety by identifying driving behavior's such as tiredness, inattention, or intoxication. The literature has demonstrated the significant significance of DMS in mitigating accidents and enhancing the safe driving experience. Drowsiness detection constitutes a fundamental component of Driver Monitoring Systems (DMS). Studies indicate tiredness impairs drivers' reactions and decision-making abilities (Dinges et al., 1997). DMS systems employ methods like eye movement and respiration pattern analysis to evaluate sleepiness levels (Wang et al., 2020). Image processing and facial recognition Image processing technologies, including infrared cameras, are employed to assess drivers' facial expressions and visual attention (Graziano et al., 2018). Deep learning has been employed to identify anomalous behaviors (Wu et al., 2022). Biometric assessment Numerous researchers have used biometric signal data, including heart rate and skin conductance, to enhance evaluation accuracy (Mehta et al., 2019; Tiwari et al., 2021). Notifications and actions DMS systems not only detect abnormalities but also inform the driver through aural signals or seat vibrations (Park et al., 2019). Obstacles and the Prospects of Document Management Systems Despite the sophistication of DMS systems, issues persist, including user privacy concerns and elevated costs. Future research may enhance the system's compatibility with driverless vehicles (Chen et al., 2023). Synopsis: The Driver Monitoring System is a device that improves driving safety by identifying and assessing driver behaviors. Nonetheless, additional study is required to mitigate constraints and enhance the system's effectiveness.

Driver Behaviors Risk Assessment System Utilizing Raspberry Pi

The Raspberry Pi is a compact, economical, and versatile computing board. It has been utilized in systems for detecting driver behaviors, including tiredness, distraction, and dangerous actions. These devices enhance road safety and possess the potential for future advancement. The Raspberry Pi has been utilized to identify hazards posed by drivers on the road. The Raspberry Pi-based system can analyze signals from cameras and sensors to detect eye blinks and yawns, which indicate driver fatigue (Sharma & Singh, 2020). Divertissement The Raspberry Pi is capable of real-time image processing to assess the driver's gaze and issue alerts when hazardous behaviors, such as mobile device usage, are identified (Reddy et al., 2021). Detection of alcohol consumption The system may be outfitted with an alcohol sensor, and the Raspberry Pi may be utilized to evaluate the breath alcohol concentration. It is additionally linked to the vehicle ignition

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 963 – 976
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5901

locking mechanism (Kumar et al., 2019). Data processing using Machine Learning Research has established a system that employs Raspberry Pi in conjunction with Machine Learning models, including Random Forest and CNN, to analyze driver behaviors in real-time (Zhang et al., 2022). Consolidation of notification systems Raspberry Pi-based systems are frequently included with alert mechanisms, such auditory signals or notifications to pertinent individuals during emergencies (Lee & Park, 2021). Despite the cost and developmental advantages of Raspberry Pi, future advancements are necessary to enhance its capacity for processing substantial data and mitigating physical damage (Patel et al., 2023).

Fig 2. Driver behaviors Risk Assessment System Utilizing Raspberry Pi

Conceptual Framework and Hypothesis Development

This study analyses the management system for transnational commercial transportation at the Nong Khai border post. This research aims to create a prototype AI system for managing cross-border freight transport by utilizing the system to identify risks associated with driver behaviors and provide safety alerts within the cross-border commercial transportation management framework. The goals are: 1. To examine the determinants influencing accidents, 2. To create an AI system to minimize accidents in terrestrial transportation, a case study of the Nong Khai border checkpoint, and 3. To evaluate the incidence of accidents before and after implementing the AI system aimed at mitigating accidents in terrestrial transportation.

The investigation into implementing a risk detection system based on driver behaviors and safety warnings within the road transport management system constitutes a survey research study. The data were obtained using a questionnaire. The sample population comprised 400 agricultural product entrepreneurs. The data were examined utilizing descriptive statistics, frequency distribution with percentages, arithmetic mean, standard deviation, and inferential statistics. The analytical methods employed were Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM). The research model underwent evaluation for model fit. The researcher evaluated the model's fit with the empirical data (Assessment of Model Fit). The indices employed to evaluate the model's fit with the empirical data comprised the Chi-Square index, CMIN/df, CFI, GFI, IFI, NFI, AGFI, RMSEA, and RMR. The model fit criteria were employed to analyze the data using a pre-existing statistical software application. The findings of the data analysis and interpretation were displayed in tabular format accompanied by explanations.

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 963 – 976
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5901

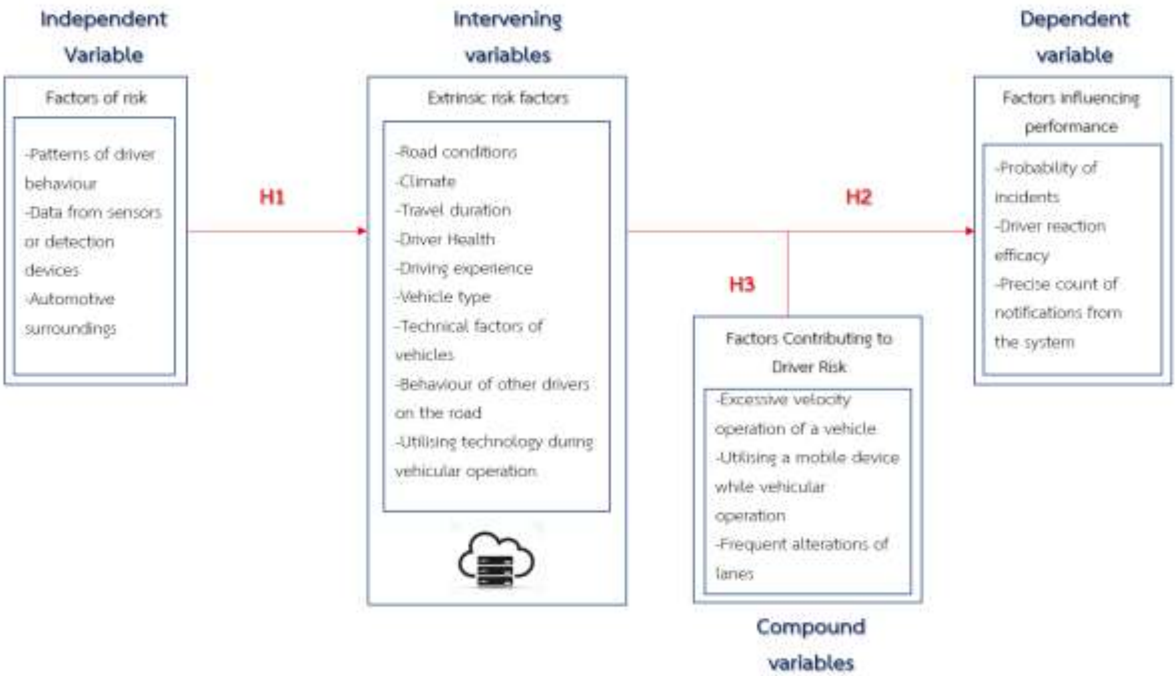

Fig 3. Conceptual Framework of Implementation of Driver Behaviors Risk Detection and Safety Alert System in Road Transport Management: A Case Study of Nong Khai Border Checkpoint

Table 2. Measurement Used in the Study

Variable	Measurement		Adapted from
Independent Variable	BUSIN1	Patterns of driver behaviors	Factors of risk
	BUSIN2	Data from sensors or detection devices	Factors of risk
	BUSIN3	Automotive surroundings	Factors of risk
Intervening variables	VALUE1	Road conditions	Extrinsic risk factors
	VALUE2	Climate	Extrinsic risk factors
	VALUE3	Travel duration	Extrinsic risk factors
	VALUE4	Driver Health	Extrinsic risk factors
	VALUE5	Driving experience	Extrinsic risk factors
	VALUE6	Vehicle type	Extrinsic risk factors
	VALUE7	Technical factors of vehicles	Extrinsic risk factors
	VALUE8	behaviors of other drivers on the road	Extrinsic risk factors
	VALUE9	Utilising technology during vehicular operation	Extrinsic risk factors
Compound variables	CSR1	Excessive velocity operation of a vehicle	Factors Contributing to Driver Risk
	CSR2	Utilising a mobile device while vehicular operation	
	CSR3	Frequent alterations of lanes	
Dependent variable	VACOCR1	Probability of incidents	Factors influencing performance
	VACOCR2	Driver reaction efficacy	
	VACOCR3	Precise count of notifications from the system	

Outcomes of Comprehensive Data Analysis on the Sample Organization

This document presents the study of general information on the organization, encompassing the nature of the business, the category of products/services offered, and the scale of the enterprise. The outcomes of the analysis are as follows:

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 963 – 976
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5901

Table 3. The Analysis Results of the General Data from the Sample Group of 400 Organizations

Overview of the organization		Quantity	Percentage
Type of business	Agriculture	70	17.50
	Agricultural processing	81	20.25
	Agricultural industry	86	21.50
	Wholesale/retail	68	17.00
	Services	47	11.75
	Transportation	15	3.75
	Warehouse	12	3.00
	OTOP	15	3.75
	Other types	6	1.50
	Total	**400**	**100.00**
Type of product/service	Agricultural export services by air and sea	60	15.00
	Goods release services	35	8.75
	Air-conditioned storage and temperature-controlled buildings	24	6.00
	Shipping Agent services	25	6.25
	Freight Forwarding services	49	12.25
	Sorting and packaging facilities	35	8.75
	Product display services	31	7.75
	Export and financial consulting services	58	14.50
	Fumigation, steaming and coating services	29	7.25
	Market information services	28	7.00
	Product sourcing services for exporters	26	6.50
	Total	**400**	**100.00**
Business size	Number 1 - 20 people	97	24.25
	Number 21 - 50 people	115	28.75
	Number 51 - 100 people	85	21.25
	Number 101 - 200 people	75	18.75
	More than 200 people	28	7.00
	Total	**400**	**100.00**

The analysis results of the general data from the sample group of 400 organizations' can be summarized as follows: The predominant business type was the agricultural industry, comprising 86 individuals or 21.50 percent, followed by agricultural processing with 81 individuals or 20.25 percent, agriculture with 70 individuals or 17.50 percent, wholesale/retail with 68 individuals or 17.00 percent, services with 47 individuals or 11.75 percent, transportation and OTOP with 15 individuals or 3.75 percent, and warehousing with 12 individuals or 3.00 percent. The least represented category was other types, account The predominant types of products or services were agricultural product export services, both by air and sea, including 60 individuals or 15.00 percent, followed by export and financial consultancy services with 58 individuals or 14.50 percent, and goods forwarding services with 49 individuals or 1.50 percent. Sorting, packaging, and product release services employed 35 individuals, representing 8.75 percent; product display services engaged 31 individuals or 7.75 percent; fumigation, steaming, and surface coating services involved 29 individuals, accounting for 7.25 percent; market condition information services utilized 28 individuals, constituting 7.00 percent; product sourcing services for exporters comprised 26 individuals or 6.50 percent; and export agent services (Shipping Agent) included 25 individuals, equating to 6.25 percent. The least represented were air-conditioned storage container services, with 24 air-conditioned buildings, which accounted for 6.00 percent. The analysis of business size revealed that the category of 21 to 50 employees was the most prevalent, comprising 115 individuals, or 28.75 percent. This was followed by the 1 to 20 employees category, which included 97 individuals, accounting for 24.25 percent. The 51 to 100 employee's

Volume: 4, No: 1, pp. 963 – 976
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5901

categories encompassed 85 individuals, representing 21.25 percent, while the 101 to 200 employee's categories contained 75 individuals, making up 18.75 percent. The category with the fewest employees, exceeding 200, included 28 individuals, constituting 7.00 percent.

Table 4. Displays Statistical Findings from Study Concerning Variables and Their Interrelationships Through Structural Equation Modeling (SEM) Analysis

Variables	λ	SE.	t-value	R^2	AVE	CR.
BUSIN1	0.99	0.11	10.172**	89.00%	0.516	0.835
BUSIN2	0.92	0.09	10.096**	84.00%	0.509	0.795
BUSIN3	1.03	N/A	N/A	107.00%	0.529	0.813
VALUE1	0.66	N/A	N/A	44.00%	0.747	0.898
VALUE2	0.76	0.05	13.511	58.00%	0.633	0.911
VALUE3	0.80	0.07	14.559	64.00%	0.817	0.931
VALUE4	1.00	0.07	12.098	101.00%	0.648	0.916
VALUE5	1.01	0.08	14.871	102.00%	0.794	0.951
VALUE6	0.92	0.07	15.185	84.00%	0.877	0.980
VALUE7	0.85	0.07	14.742	73.00%	0.779	0.933
VALUE8	0.96	0.05	18.540	92.00%	0.683	0.895
VALUE9	0.74	0.05	14.379	55.00%	0.591	0.876
CSR1	0.92	0.06	15.977	84.00%	0.858	0.968
CSR2	0.93	0.05	15.541	87.00%	0.796	0.938
CSR3	0.84	N/A	N/A	71.00%	0.562	0.835
VACOCR1	0.97	N/A	N/A	95.00%	0.594	0.814
VACOCR2	0.99	0.05	16.17	99.00%	0.630	0.894
VACOCR3	0.62	0.06	12.333	39.00%	0.731	0.915

The table presents the statistical findings from research concerning variables and their interrelationships, employing Structural Equation Modelling (SEM) to assess various metrics, including relative weight (λ), standard error (SE), t-value, $R2$ value, average variance extracted (AVE), and composite reliability (CR) of the observed variables that serve as indicators of the latent structure. The study of the data in the table indicates that

λ (Lambda): The relative weight (or factor loading) signifies the association between observed variables and latent constructs. Elevated values (approaching 1) signify that the observable variable significantly contributes to the latent construct being assessed. SE (Standard Error): The standard error signifies the degree of uncertainty in the estimate. Minimal values denote accurate forecasts. t-value: Employed to assess the significance of the association. A t-value of 1.96 (for a significance level of 0.05) or 2.576 (for a significance level of 0.01) signifies a substantial association. R^2 (Coefficient of Determination): The ratio of the variance in the observed variable that can be elucidated by the latent construct. Elevated values (approaching 1) signify that the latent construct effectively elucidates the observed variable. AVE (Average Variance Extracted): The mean variance that the latent variable can elucidate regarding the indicators. Values exceeding 0.5 signify robust construct validity. Composite Reliability (CR) denotes the consistency of indicators across latent constructs. A number exceeding 0.7 signifies adequate confidence.

BUSIN: Indicators BUSIN1 to BUSIN3 have elevated λ values (0.92 - 1.03) and substantial t-values (** denotes a significance level of 0.01), except BUSIN3, which lacks SE and t-values but possesses a $R2$ as high as 107%. This construct's AVE and CR scores fall within an acceptable range (0.516 - 0.835). VALUE: Indicators VALUE1 to VALUE9 have comparatively elevated λ values (0.66 - 1.01). The t-values are significant, except a few unspecified instances. The AVE and CR scores exceed the conventional thresholds of 0.5 and 0.7, respectively, indicating strong validity and reliability. CSR: Indicators CSR1 to CSR3 exhibit λ values ranging from 0.84 to 0.93, accompanied by substantial t-values, elevated AVE, and CR values. 0.796 to 0.968 demonstrates strong consistency and reliability of the VACOCR indicators: The VACOCR1

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 963 – 976
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5901

to VACOCR3 indicators exhibit a broad spectrum of λ values (0.62 - 0.99), with considerable t-values, and the AVE and CR values are commendably satisfactory (0.594 - 0.915).

The majority of the observed variables exhibited elevated factor loadings and significant t-values, indicating strong measurement validity. The AVE and CR values for the majority of latent constructs met the established criteria, demonstrating strong validity and reliability of the assessment tools. The statistics indicate a strong alignment of the model in this investigation.

Table 5. Confirmatory Factor Analysis (CFA)

Variables	Measure	$\bar{X}$	SD.	λ	SE.	t-value	R^2
BUSIN1	ADMI1	4.00	0.83	0.48	0.08	10.042**	48.10%
	ADMI2	4.10	0.79	0.86	0.09	13.919**	74.30%
	ADMI3	4.04	0.84	0.91	0.11	13.120**	82.90%
	ADMI4	4.20	0.87	0.66	0.05	21.122**	43.10%
	ADMI5	4.21	0.85	0.59	-	-	34.60%
BUSIN2	OPER1	4.16	0.81	0.62	0.08	12.298**	38.70%
	OPER2	4.06	0.91	1.00	0.13	12.953**	100.50%
	OPER3	4.14	0.86	0.59	0.06	17.162**	34.40%
	OPER4	4.24	0.88	0.55	-	-	29.90%
BUSIN3	SUPP1	4.25	0.81	0.60	0.10	10.916**	35.90%
	SUPP2	4.27	0.86	0.93	0.12	14.112**	86.40%
	SUPP3	4.14	0.85	0.73	0.08	14.726**	53.20%
	SUPP4	4.19	0.76	0.60	-	-	36.40%
VALUE1	INBO1	4.12	0.81	0.75	0.04	20.779	56.30%
	INBO2	4.16	0.93	0.95	0.04	29.478	89.30%
	INBO3	4.17	0.93	0.89	-	-	78.70%
VALUE2	WORK1	4.01	0.88	0.81	0.09	16.292	64.90%
	WORK2	4.10	0.77	0.60	-	-	35.90%
	WORK3	3.95	1.06	0.78	0.13	13.177	60.00%
	WORK4	4.09	0.94	0.86	0.11	15.543	74.60%
	WORK5	4.06	0.96	0.89	0.11	16.874	78.60%
	WORK6	4.18	0.96	0.81	0.12	13.967	66.10%
VALUE3	OUBT1	3.99	0.85	0.91	0.04	25.783	82.50%
	OUBT2	4.07	0.65	0.87	0.03	31.712	75.90%
	OUBT3	4.08	0.83	0.93	-	-	86.90%

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 963 – 976
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5901

VALUE4	SERV1	4.08	0.91	0.75	0.11	13.702	52.90%
	SERV2	4.11	0.91	0.73	0.10	14.365	53.70%
	SERV3	4.37	0.83	0.93	0.11	15.893	86.30%
	SERV4	4.36	0.86	0.88	0.11	14.919	86.10%
	SERV5	4.42	0.71	0.85	0.09	15.380	72.00%
	SERV6	4.23	0.71	0.66	-	-	43.60%
VALUE5	SALE1	4.40	0.82	0.93	0.05	25.021	86.10%
	SALE2	4.41	0.83	0.93	0.04	26.102	98.90%
	SALE3	4.46	0.67	0.90	0.04	24.472	80.70%
	SALE4	4.42	0.73	0.87	0.04	22.634	75.90%
	SALE5	4.28	0.85	0.82	-	-	66.70%
VALUE6	STRU1	4.16	0.86	0.81	0.06	18.062	35.90%
	STRU2	4.38	0.82	0.93	0.04	30.286	87.30%
	STRU3	4.42	0.81	0.98	0.04	32.467	95.70%
	STRU4	4.48	0.67	0.93	0.03	36.051	86.00%
	STRU5	4.50	0.65	0.97	-	-	93.90%
	STRU6	4.39	0.83	1.00	0.05	28.129	59.80%
VALUE7	HUMA1	4.26	0.75	0.75	0.05	16.497	34.20%
	HUMA2	4.45	0.70	0.85	0.03	29.180	71.80%
	HUMA3	4.47	0.69	0.96	0.02	44.398	91.30%
	HUMA4	4.44	0.70	0.96	-	-	92.30%
VALUE8	TECH1	4.47	0.69	0.85	0.07	16.367	72.90%
	TECH2	4.38	0.83	0.90	0.08	18.456	80.40%
	TECH3	4.41	0.71	0.83	0.07	16.986	69.30%
	TECH4	4.01	0.72	0.71	-	-	50.50%
VALUE9	PROV1	4.00	0.96	0.74	0.09	14.385	55.30%
	PROV2	4.18	0.79	0.64	0.07	13.350	41.00%
	PROV3	4.28	0.75	0.80	0.07	15.353	63.50%
	PROV4	4.17	0.87	0.96	0.09	17.785	91.40%
	PROV5	4.17	0.83	0.66	-	-	44.10%
CSR1	COMM1	4.11	0.91	0.86	0.06	20.669	48.80%
	COMM2	4.37	0.83	0.98	0.04	34.720	95.50%

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 963 – 976
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5901

	COMM3	4.36	0.86	0.93	0.04	30.352	87.10%
	COMM4	4.42	0.71	0.88	0.03	31.080	76.80%
	COMM5	4.45	0.66	0.98	-	-	95.80%
CSR2	ENVI1	4.36	0.79	0.99	0.10	15.692	97.30%
	ENVI2	4.45	0.64	0.97	0.08	15.584	94.30%
	ENVI3	4.47	0.66	0.92	0.08	14.841	84.70%
	ENVI4	4.04	0.82	0.65	-	-	41.90%
CSR3	ECON1	4.17	0.81	0.89	0.06	17.264	78.40%
	ECON2	3.96	0.93	0.68	0.05	16.200	46.80%
	ECON3	4.08	0.91	0.63	0.05	17.213	39.50%
	ECON4	4.10	0.95	0.78	-	-	60.30%
VACOCR1	CLUS1	4.14	0.83	0.70	0.05	15.786	49.10%
	CLUS2	4.19	0.87	0.74	0.05	17.212	55.10%
	CLUS3	4.06	0.84	0.86	-	-	74.20%
VACOCR2	CHAI1	4.04	0.93	0.81	0.08	16.425	64.90%
	CHAI2	4.12	0.82	0.70	0.06	15.097	48.90%
	CHAI3	4.24	0.74	0.82	-	-	64.20%
	CHAI4	4.19	0.88	0.91	0.06	21.002	83.40%
	CHAI5	4.15	0.84	0.71	0.07	14.1	47.40%
VACOCR3	CREA1	4.11	0.89	0.70	0.05	16.512	48.90%
	CREA2	4.28	0.84	0.95	0.03	31.071	91.00%
	CREA3	4.23	0.89	0.91	-	-	82.40%
	CREA4	4.26	0.86	0.84	0.04	24.113	70.00%

Factors of risk: The analysis results of variables in the application model for driver behavior risk detection and warning systems within the road transport management system. The model's consistency regarding risk was assessed by confirmatory factor analysis. The study of the second-order confirmatory factors revealed that the confirmatory factor model was congruent with the empirical data, evidenced by Chi-Square = 34.406, df = 25, Sig. = 0.100 > 0.05, and CMIN/df = 1.376 < 5.0. The analysis demonstrated consistency and yielded statistical values: the comparative fit index (CFI) was 0.998, exceeding 0.90; the goodness of fit index (GFI) was 0.987, surpassing 0.90; the adjusted goodness of fit index (AGFI) was 0.953, exceeding 0.80; the root mean square error of approximation (RMSEA) was 0.031, below 0.05; the root mean square residual (RMR) was 0.021, below 0.05; the normed fit index (NFI) was 0.994, exceeding 0.90; and the incremental fit index (IFI) was 0.998, surpassing 0.90. All seven indices met the established criteria.

External risk factors and the analysis of variables in the application model for a driver behavior risk detection and warning system inside road transport management. Extrinsic risk factors Consequently, the model's reliability was assessed by second-order confirmatory factor analysis. The model demonstrated a

Volume: 4, No: 1, pp. 963 – 976
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5901

strong alignment with the empirical data, evidenced by Chi-Square = 868.197, df = 449, Sig. = 0.000, and CMIN/df = 1.934, which is less than 5.0. The model demonstrated consistency with statistical values: comparative fit index (CFI) of 0.984 > 0.90, goodness of fit index (GFI) of 0.905 > 0.90, adjusted goodness of fit index (AGFI) of 0.810 > 0.80, root mean square error of approximation (RMSEA) of 0.048 < 0.05, and root mean square error of standardized residuals (RMR) of 0.048 < 0.05. Additionally, the normed fit index (NFI) was 0.967 > 0.90, and the incremental fit index (IFI) was 0.984 > 0.90, all of which met the established criteria for the seven indices.

Driver Risk Factors: An Analysis of Variables in the Application Model for Driver Behavior Risk Detection and Warning Systems in Road Transport Management Consequently, the model's reliability was assessed by second-order confirmatory factor analysis. The model demonstrated a satisfactory alignment with the empirical data, evidenced by Chi-Square = 41.212, df = 29, Sig. = 0.066 > 0.50, and CMIN/df = 1.421 < 5.0. The model demonstrated consistency with statistical values: comparative fit index (CFI) of 0.998 (> 0.90), goodness of fit index (GFI) of 0.985 (> 0.90), adjusted goodness of fit index (AGFI) of 0.952 (> 0.80), root mean square error of approximation (RMSEA) of 0.032 (< 0.05), and root mean square residual (RMR) of 0.019 (< 0.05). Additionally, the normed fit index (NFI) was 0.993 (> 0.90), and the incremental fit index (IFI) was 0.998 (> 0.90), all meeting the established criteria across the seven indices.

Performance determinants for implementing a driver behavior risk detection and warning system in road transport safety management. The outcome of the examination of factors inside the value co-creation model incorporating the value chain and corporate social responsibility. The dependent variable pertains to the dimension of value co-creation concerning the value chain and corporate social responsibility. Consequently, the consistency of the second-order confirmatory model was assessed. The analytical results strongly aligned with the empirical data, evidenced by Chi-Square = 24.160, df = 28, Sig. = 0.673 > 0.50, and CMIN/df = 0.863 < 5.0. The analysis demonstrated consistency, with the following statistical values: comparative fit index (CFI) of 1.000 (> 0.90), goodness of fit index (GFI) of 0.990 (> 0.90), adjusted goodness of fit index (AGFI) of 0.972 (> 0.80), root mean square error of approximation (RMSEA) of 0.000 (< 0.05), root mean square error of standardized residuals (RMR) of 0.013 (< 0.05), normed fit index (NFI) of 0.994 (> 0.90), and incremental fit index (IFI) of 1.001 (> 0.90). All seven indices met the established criteria.

Table 6. Presents the Statistical Metrics for Evaluating the Fit of the Structural Equations in the Value Co-Creation Model, Incorporating the Value Chain And Corporate Social Responsibility Following Model Adjustment

Index	Criteria	Result	Conclusion	แนวคิดในการอ้างอิง
Chi –Square	p. > 0.05	70.920	Complies	Hair et al. (1998;2006) , Bollen (1989) and Sorbon (1996)
CMIN/df.	< 5.0	8.864	Complies	Bollen (1989) , Diamantopoulos , Siguaw (2000)
GFI	≥ 0.90	0.981	Complies	Hair et al. (1998;2006),Browne and Cudeck (1993)
AGFI	≥ 0.90	0.944	Complies	Durande-Moreau an Usunier(1999), Harrison walker(2001)
NFI	≥ 0.90	0.994	Complies	Hair et al. (1998;2006) , Mueller (1996)
IFI	≥ 0.90	0.999	Complies	Hair et al. (1998;2006) , Mueller (1996)
CFI	≥ 0.90	0.999	Complies	Hair et al. (1998;2006) , Mueller (1996)
RMR	< 0.05	0.009	Complies	Diamantopoulos , Siguaw (2000)
RMSEA	< 0.05	0.025	Complies	Hair et al. (1998;2006),Browne and Cudeck (1993)

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 963 – 976
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5901

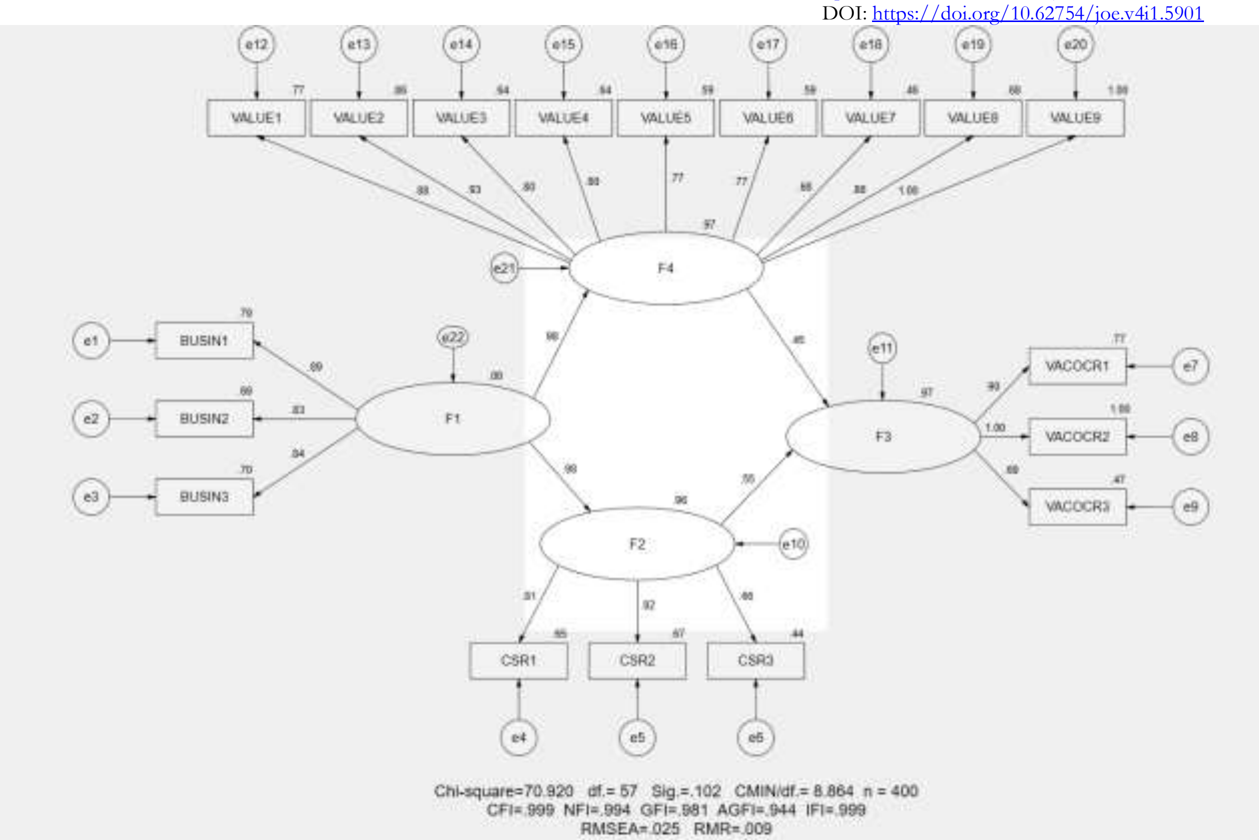

Fig 4. Structural Equation Modeling of Value Co-Creation in Relation to the Value Chain and Corporate Social Responsibility Following Model Modification

Discussion

The analysis revealed that the structural equation model for the driver behavior risk detection system and safety warning within the road transport management system demonstrated a strong alignment with empirical data, in accordance with the principles established by Hair et al. (1998; 2006), Bollen (1989), and Sorbon (1996). This is evidenced by a Chi-Square value of 70.920, degrees of freedom (df) = 57, significance (Sig.) = $0.102 > 0.05$, and a CMIN/df ratio of $8.864 < 5.0$. The study of the model modification revealed that seven indices were consistent, with their statistical values meeting the established criteria for all indices, as detailed below.

The Comparative Fit Index (CFI) study result is 0.999, which exceeds 0.90. The index value aligns with the principles established by Hair et al. (1998; 2006), which stipulate that an acceptable CFI should be 0.90 or above, signifying a relative model fit. The Goodness of Fit Index (GFI) quantifies the variance and covariance accounted for by the model, with an analysis result of 0.981, exceeding the threshold of 0.90. The index value aligns with the principles established by Hair et al. (1998; 2006) and Mueller (1996), which stipulate that an acceptable Goodness of Fit Index (GFI) should be 0.90 or greater, signifying a relative model fit. The adjusted goodness of fit index (AGFI) reflects the variance and covariance accounted for by the model, corrected for degrees of freedom. The AGFI value typically ranges from 0 to 1, with an acceptable threshold exceeding 0.90. The analysis result is 0.944, which exceeds 0.90. The index result aligns with the Durande-Moreau and Usunier (1999) notion, which posits that a satisfactory AGFI should be 0.90 or above, signifying a relative model fit. The Root Mean Square Error of Approximation (RMSEA) is a statistic employed in hypothesis testing. An optimal RMSEA value should be below 0.05 or within the range of 0.05 to 0.08, signifying that the model aligns well with the actual data. The analysis result is 0.025, which is less than 0.08, indicating an excellent RMSEA score. The index value aligns with the notion as per the criteria established by Hair et al. (1998; 2006) and Browne and Cudeck (1993), suggesting that the

Journal of Ecohumanism
2025
Volume: 4, No: 1, pp. 963 – 976
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
DOI: https://doi.org/10.62754/joe.v4i1.5901

model exhibits relative fit. The comparative fit index in its independent form (Normed Fit Index; NFI) is a statistic utilized for hypothesis testing. The allowable NFI value must exceed 0.90. The study yields a result of 0.994, which exceeds 0.90. The index value aligns with the framework proposed by Hair et al. (1998; 2006), suggesting that the model exhibits a relative fit. The Incremental Fit Index (IFI) evaluates the comparative performance of a test model against a baseline model, where all variables are uncorrelated. A score exceeding 0.90 signifies that the theoretical model effectively elucidates the relationships among the variables. The acceptable IFI value must exceed 0.90, and the analytical result is 0.999, more considerable than 0.90. The index result aligns with the framework proposed by Hair et al. (1998; 2006), suggesting that the model exhibits a relative fit. The Root Mean Square Residual (RMR) is a statistic employed to evaluate the hypothesis. The RMR value must be below 0.05, with an optimal value being zero or near 0. The analysis yields an RMR value of 0.009, much less than 0.05, indicating an excellent RMR. The index result aligns with the principles and criteria Diamantopoulos and Siguaw (2000) established, suggesting that the model exhibits a relative match.

Research Implications

The analysis of the seven index values aligns with the empirical data, demonstrating that the structural equation model for the driver behavior risk detection and warning system in road transport management is statistically acceptable. Consequently, it can be inferred that the variables in the model for implementing the driver behavior risk detection and warning system for road transport safety comprise risk factors, external risk factors, and external risk factors. The dependent variables of the driver behavior risk detection and warning system for road transport management align with the requirements for value determination, indicating that this measurement model possesses validity or acceptable fit confirmation.

Table 7. Results of Structural Equation Analysis of the Causal Model of Applying the Driver Behavior Risk Detection and Warning System For Safety in the Road Transport Management System.

Variable (relationship dyad)			λ	SE.	t-value	Sig.	R^2
Extrinsic risk factors	<--	Factors of risk	0.99	0.06	24.482	0.000**	98.00%
Factors Contributing to Driver Risk	<--	Factors of risk	0.97	0.06	14.246	0.000**	95.00%
Extrinsic risk factors	<--	Factors Contributing to Driver Risk	0.58	0.19	4.320	0.000**	97.00%
Extrinsic risk factors	<--	Factors influencing performance	0.42	0.12	3.347	0.000**	97.00%

** Statistically significant at $p < 0.001$

The outcomes of the structural equation analysis of the causal model, incorporating the regression coefficients of the independent variables expressed as standard scores, which serve as the decision coefficient to denote variable influence, with statistical significance at 0.001, are summarized as follows: Risk factors comprise three latent variables: high-speed driving, cell phone usage while driving, and frequent lane changes, with regression coefficient weights ranging from 0.77 to 0.93. The test results indicated that risk factors affect the structural model of the driver behavior risk detection system and safety warning application in road transport management, directly influencing two aspects. External risk factors comprise three latent variables with regression coefficient weights ranging from 0.68 to 1.00. The test results indicated that external risk factors affect the structural model of the driver behavior risk detection system and safety alert application within the road transport management system. The risk factor from drivers, influenced directly by one variable, has three latent variables with regression coefficient weights ranging from 0.66 to 0.82. The test results indicated that the corporate social responsibility component significantly impacts the elucidation of the structural model for creating shared value, demonstrating a direct influence of 1 on the value chain and corporate social responsibility. The risk factor associated with drivers positively influences the efficiency factor, evidenced by a regression coefficient of 0.58, a margin of error of 0.19, a t-value of 4.320, and a significance value of 0.000, less than 0.001. The risk factor from drivers accounts for 97.00% of the structural equations of external risk and driver risk, with a statistical significance level of 0.001.

References

Chen, X., Zhang, L., & Huang, J. (2023). Advances in driver monitoring systems for autonomous vehicles. Journal of Intelligent Transportation Systems, 27(2), 102-115.
Dinges, D. F., Mallis, M. M., & Maislin, G. (1997). The dangers of drowsy driving. Sleep Research Society Bulletin, 3(1), 30-36.
Graziano, M., Montanari, R., & Grimaldi, M. (2018). Real-time face recognition in driver monitoring systems. Applied Artificial Intelligence, 32(4), 277-292.
Mehta, P., & Singh, A. (2019). Biometric data integration for driver fatigue detection. Journal of Safety Research, 70, 131-140.
Kumar, R., & Gupta, S. (2019). Alcohol detection using Raspberry Pi in driver monitoring systems. International Journal of Advanced Computer Science, 10(3), 120-128.
Lee, J., & Park, H. (2021). Real-time driver monitoring using Raspberry Pi and IoT. Sensors, 21(6), 2019.
Park, J. H., Choi, K. S., & Lee, H. (2019). Alarm systems in advanced driver monitoring. IEEE Transactions on Intelligent Vehicles, 4(3), 219-225.
Patel, A., & Desai, K. (2023). Challenges in Raspberry Pi-based driver monitoring systems. Embedded Systems Research, 15(4), 55-64.
Reddy, S., Kumar, V., & Singh, A. (2021). Driver distraction detection with Raspberry Pi and image processing. Journal of Transportation Safety, 17(2), 78-89.
Sharma, P., & Singh, R. (2020). Raspberry Pi-based drowsiness detection systems. Journal of Advanced Robotics, 23(7), 1024-1033.
Singh, M., & Gupta, V. (2022). Performance of Raspberry Pi in driver behavior monitoring. Journal of IoT Applications, 8(5), 411-422.
Tiwari, P., & Mishra, S. (2021). Physiological signal analysis in driver behavior monitoring. Biomedical Signal Processing and Control, 63, 102384.
Wang, Y., Li, H., & Zhou, X. (2020). Eye-tracking in driver fatigue detection. Computer Vision and Image Understanding, 194, 102848.
Wang, H., & Zhang, L. (2020). Integration of machine learning with Raspberry Pi for driver risk detection. IEEE Transactions on Intelligent Systems, 25(4), 543-550.
Wu, D., Wang, S., & Jiang, T. (2022). Deep learning approaches in driver monitoring. Neural Networks, 147, 55-67.
Zhang, R., Huang, W., & Lin, J. (2018). Ethical considerations in driver monitoring systems. Technology and Ethics, 14(2), 89-98.
Zhou, K., & Zhao, Q. (2021). Cost-effective driver monitoring solutions. Automotive Engineering, 18(1), 45-52.
Zhang, X., Wu, T., & Lin, J. (2022). Implementation of CNN on Raspberry Pi for real-time driver monitoring. Computer Vision in Intelligent Transportation Systems, 12(1), 65-77.
Zhou, Q., & Li, H. (2021). Low-cost driver monitoring solutions using Raspberry Pi. Automotive Engineering and AI, 19(3), 205-216.
Zhu, Y., & Wang, J. (2022). Enhancing driver safety using Raspberry Pi and multi-sensor fusion. Journal of Embedded Intelligence, 14(2), 134-145.