RESEARCH IN MANAGEMENT OF TECHNOLOGY AND BUSINESS
e-ISSN: 2773-5044

RMTB

Vol. 6 No. 1 (2025) 115-123
https://publisher.uthm.edu.my/periodicals/index.php/rmtb

The Uses of Correlation Analysis Towards Artificial Intelligence in Public Transportation to Enhance Safety and Efficiency

Mohamad Amir Firdaus Zainuddin[1], Muhammad Ammar Shafi[1]*

[1] *Department of Technology and Management/Faculty of Technology Management and Business, Universiti Tun Hussein Onn Malaysia, Batu Pahat, 86400, MALAYSIA*

*Corresponding Author: ammar@uthm.edu.my
DOI: https://doi.org/10.30880/rmtb.2025.06.01.010

Article Info

Received: 31 March 2025
Accepted: 30 April 2025
Available online: 30 June 2025

Keywords

Artificial intelligence, prediction model, transportation, forecasting.

Abstract

The application of AI-driven prediction models to improve transportation efficiency and safety is examined in this research. Artificial Intelligence (AI) enhances autonomous vehicle navigation, facilitates predictive maintenance, and optimizes traffic management by utilizing machine learning and real-time data. Important uses include preventing accidents, maintaining infrastructure, and optimizing traffic flow. The research underscores the noteworthy advantages and obstacles associated with the deployment of these technologies, stressing the necessity of sustained progress to promote more intelligent and durable transportation networks. By using the quantitative method, 375 respondents will focus on people who use public transportation in Klang Valley to answer the questionnaire. Statistical Package for Social Science (SPSS) will use to analyze the data. These results may serve as a reference to enhance the quality of the tourism sector in Malaysia.

1. Introduction

As transportation systems evolve, integrating artificial intelligence (AI) and predictive modelling becomes a critical tool for improving safety and efficiency. The rapid advancement of AI technologies has permitted the development of sophisticated prediction models capable of analysing massive volumes of data and anticipating various eventualities in transportation networks. These models provide insights into traffic patterns, vehicle behaviour, and environmental conditions, allowing for proactive decision-making and risk mitigation methods. Transportation stakeholders may use AI-driven prediction models to optimise route planning, reduce congestion, and improve overall system resilience, resulting in safer and more efficient travel experiences for people and commodities. Prior research emphasises how important AI is to improving safety. For instance, using driving 2 behaviour, road conditions, and vehicle dynamics, machine learning algorithms have been utilised to identify and forecast collisions (Zhang *et al.*, 2022). Furthermore, the use of predictive models in transportation demonstrates a trend towards proactive risk management and resource allocation. Traditional approaches frequently rely on reactive tactics, resulting in inefficiencies and safety risks. However, AI-powered prediction models allow stakeholders to anticipate possible dangers, such as accidents or infrastructure failures, and take preventative measures to limit their impact. Furthermore, these models allow for real-time modifications to transportation operations, ensuring a dynamic response to changing conditions. Transportation systems that incorporate prediction models can adapt to changing needs, minimise interruptions, and optimise resource utilisation, eventually furthering the safety and efficiency goals important to modern mobility projects. To reduce delays and fuel consumption, AI prediction models have been very useful in forecasting traffic congestion, streamlining bus schedules, and improving route planning (Chen *et al*., 2023).

Advancing technology has enhanced transportation safety with AI-driven systems. Safety measures include strict standards like regular maintenance, compliance with traffic rules, qualified operators, and advanced technologies like GPS tracking and collision avoidance. Abduljabbar *et al*. (2019) highlight using AI to identify incident time, location, and severity, aiding traffic managers in reducing congestion. This study addresses public transport safety and efficiency. Lakshmi Shankar Iyer (2021) noted that AI enhances transportation by managing design, operations, and logistics in real-time, enabling humanlike decision-making on roads. AI also estimates and analyses surroundings for driver assistance and autonomous navigation.

This study examines the impact of AI correlation analysis on public transportation in Klang Valley, chosen due to high usage per JPJ data. It focuses on reducing accidents, optimising resources, enhancing decision-making, improving system reliability, and supporting environmental sustainability. The research evaluates AI's role in accident reduction, resource optimisation, and system resilience, while assessing current AI adoption levels in transportation.

2. Literature Review

2.1 Artificial Intelligence

Artificial Intelligence (AI), first introduced by John McCarthy in 1956, aims to replicate human brain functions in machines, tackling problems beyond conventional computing. Between 1960 and 1970, researchers explored AI through artificial neural networks (ANNs) and knowledge-based systems (KBS), which use predefined rules to make recommendations. Modern AI leverages machine learning, enabling systems to learn and improve from experience without explicit programming (Murphy, 2012).

Alan Turing, considered the founder of AI, laid the foundation for artificial intelligence with his 1950 "Turing Test," which defines AI as a system exhibiting human-like behaviour. His theories also helped shape modern computing. AI-driven robotics, combining mechanical systems with intelligent algorithms, is now used in fields like manufacturing and healthcare, where precision and autonomy are essential (Siciliano & Khatib, 2016).

Marvin Minsky, a pioneer in AI, created SNARC in 1951, the first neural network simulator, and promoted a multidisciplinary approach combining computer science, psychology, and neuroscience. His 1969 book Perceptrons, co-written with Seymour Papert, influenced AI research by exploring the potential and limitations of neural networks. Minsky's work continues to shape AI advancements. Ethical concerns, including bias, privacy, and socioeconomic implications, are crucial for ensuring responsible AI development and use (Jobin, Ienca, & Vayena, 2019).

Safety involves implementing policies and procedures to reduce hazards, with guidance from the Occupational Safety and Health Administration (OSHA). Process efficiency can be achieved through technology, streamlined procedures, and resource management, with Lean Six Sigma being a key approach for waste reduction and improved flow. A study in the *Journal of Safety Research* emphasizes that integrating safety and efficiency can boost operational effectiveness and productivity (Smith & Wesson, 2020).

2.2 Artificial Intelligence (AI) components

For the AI to support and carry out the function, the component of the AI needs to be working perfectly. In this part, a few components of AI are listed as explained in detail referring to the research article reviewed.

2.2.1 Machine Learning Algorithms

From "Machine Learning: A Probabilistic Perspective" by Kevin P. Murphy, Many AI systems are built around machine learning techniques. These techniques free computers from explicit programming for every activity, allowing them to learn from data, see patterns, and make judgements. Common machine learning strategies include reinforcement learning, supervised learning, and unsupervised learning.

2.2.2 Natural Language Processing (NLP)

From "Natural Language Processing with Python" by Steven Bird, Ewan Klein, and Edward Loper, NLP is concerned with making computers capable of comprehending, interpreting, and producing human language. It includes things like sentiment analysis, text summarization, language translation, and speech recognition. Large volumes of textual data must frequently be parsed and analysed when using NLP techniques.

2.2.3 Computer Vision From

"Deep Learning for Computer Vision" by Rajalingappaa Shanmugamani, Machines can read and comprehend visual data from the actual world thanks to computer vision. It includes things like segmenting images, classifying images, identifying faces, and detecting objects. In computer vision tasks, convolutional neural networks, or CNNs, are frequently employed.

2.3 Artificial Intelligence in Transportation

According to Chen *et al*. (2021), AI-driven traffic management systems significantly reduce congestion and enhance traffic flow by leveraging predictive analytics, real-time monitoring, and optimization algorithms. AI uses historical data to predict traffic patterns, continuously evaluates real time sensor and camera data to manage traffic and employs algorithms to adjust signals and suggest alternative routes efficiently.

According to Abduljabbar *et al.* (2019) in *Applications of Artificial Intelligence in Transport: An Overview*, AI offers effective solutions for managing complex transportation systems. AI-powered smart agents, such as traffic sensors, can predict traffic conditions and detect accidents automatically. Techniques like Artificial Neural Networks (ANNs) are widely used for traffic incident detection, road planning, public transport, and traffic prediction. ANNs are divided into supervised methods (e.g., SVM, PNN, RBN, K-Nearest Neighbours, Decision Trees) and unsupervised methods (e.g., cluster analysis, greedy layerwise training).

According to Sony, Astya, and Bhushan in *Revolutionizing Transportation System Using Artificial Intelligence Technique*, AI addresses global transportation challenges caused by rising populations and vehicle numbers. By leveraging real-time data, AI optimizes traffic management, enhances mobility, and integrates executive traffic control for efficiency. Recognized as a top emerging technology by the World Economic Forum, AI improves system productivity, economic efficiency, and trip predictability, offering significant opportunities for sustainable advancements in transportation.

2.4 Conceptual Framework

Fig. 1 shows the research framework of perception of safety, passenger satisfaction and adoption of AI in public transportation with safety and efficiency. The hypotheses are as proposed below.

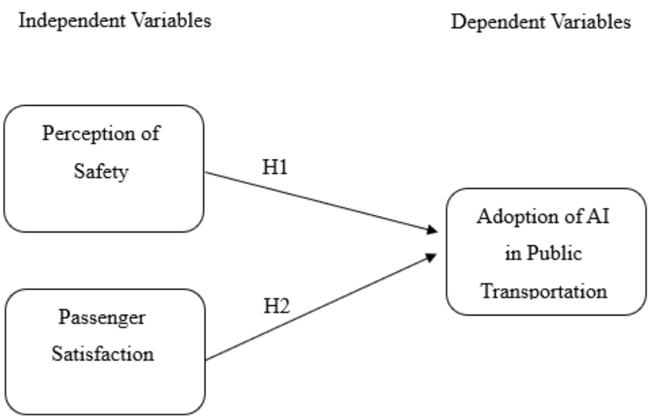

Fig. 1 *Research Framework*

H1: There is a significant relationship between perception of safety and the adoption of AI in public transportation.
H2: There is a significant relationship between passenger satisfaction and the adoption of AI in public transportation.

3. Research Methodology

In research, a traditional research design, as described by Thyer (1993), outlines the plan for conducting a study, including operationalising variables, selecting a study sample, collecting data, testing hypotheses, and analysing results. It establishes reliable, valid, and accurate research techniques, as Kumar (2011) highlights.

The study conducted a literature review on Artificial Intelligence (AI) and its application in transportation, utilizing secondary data from written and electronic sources. Additionally, primary data was collected through surveys using a questionnaire developed by the researcher, distributed both in print and via Google Forms.

The study has three objectives: (i) assess the impact of AI prediction models in transportation on accident reduction and resource optimisation, (ii) examine how AI prediction models influence decision-making and operational strategies for system reliability and resilience, and (iii) evaluate the contribution of AI prediction models to environmental sustainability and carbon emission reduction.

The study utilised questionnaires to collect data from randomly selected people who use public transportation in Klang Valley. Data analysis, including reliability, descriptive, normality tests, and correlation, was conducted using SPSS software to achieve research objectives.

Statistical techniques, such as multiple regression, examine connections between independent and dependent variables and quantify trends. These techniques help researchers accept or reject study hypotheses establishing relationships between variables. Quantitative approaches, often utilizing surveys or questionnaires, isolate independent variables to observe changes in dependent variables (Rudestam & Newton, 2015).

3.1 Unit of Analysis

The person or item throughout the data-gathering phase in the research is referred to as the unit of analysis. Individuals, groups, organisations, social artefacts, and social interactions were the four kinds of unit of analysis. The person is the unit of analysis in this study among transport users in Klang Valley. 6 The study focuses on the factors AI in transportation influencing users' transportation in Klang Valley. Individuals who use public transportation were the study's target respondents.

3.2 Population and Sampling

The research population is defined as those who appeal to the researcher's desire to generalise the study's findings, and the population may also refer to the entire number of persons, organisations, objects, or products from whom samples are chosen (Kindy *et al*., 2016). The term population refers to the entire group of people to whom the research was applied. The study targets daily public transportation users in Klang Valley, aged 18 and above, with a population estimated at 4.5 to 5 million in 2024. Simple random sampling was employed, ensuring each member had an equal chance of selection. With a total of 384 samples, the study aims to provide a reliable representation of the population, chosen using Krejcie and Morgan's approach at a 95% confidence level.

Sampling, the process of determining the sample size for respondents, encompasses three approaches: probability sampling, non-probability sampling, and mixed sampling. For this study, probability (random) sampling is optimal as it aims to generalise findings to the entire population. Random sampling, as described by Kumar (2011), involves selecting subjects randomly from a potential pool to ensure every member of the population has an equal and independent chance of inclusion. For this study, a basic random sampling method was utilized, where participants were randomly selected from Klang Valley transportation users using a fishbowl draw. This approach ensures equal and independent probabilities of selection for all transportation users in Klang Valley.

Any empirical study that aims to make inferences about a population from a sample must consider the significance of the sample size (Hamed, 2017). Krejcie and Morgan (1970) assert that to accurately reflect the complete population, a sample must be taken. Based on the chart created by Krejcie and Morgan (1970), about 375 respondents make up the study's sample size.

3.3 Data Collection Procedure

Primary data and secondary data were the two types of data that been used in the research to gather the information about the topic. The study collected primary data through questionnaires, interviews, and observations, considered reliable methods (Kabir, 2016; Ajayi, 2017). A closed-question questionnaire was developed, validated by the Faculty of Technology Management & Business at University Tun Hussein in Malaysia, and distributed to 375 randomly selected Klang Valley residents via paper and Google Forms. Most responses were gathered online for convenience, with data analysed using SPSS to explore relationships between variables. Despite some uncooperative respondents, the researcher successfully completed the data collection over two months.

3.4 Data Analysis

Pilot studies, as noted by Joy *et al*. (2018), serve to pre-test research instruments and ensure the feasibility of larger investigations. Kumar (2011) emphasizes the importance of conducting pilot tests to guarantee the quality and accuracy of data before actual data collection. In this study, a reliability test is employed as a pilot test to ensure the trustworthiness of the research instrument. Consistency in administering the test to a subset of individuals from the study population enhances measurement precision and reliability, as outlined by Kumar (2011).

Reliability analysis assesses the internal consistency and reliability of variables. Its aim is to examine consistency between pilot and real studies. According to Sekaran and Roger (2016), Cronbach's Alpha values of 1.00 indicate complete reliability, while values below 0.00 indicate untrustworthy questionnaires. The range of 0.80 to 0.90 is commonly used in most studies.

Descriptive statistics, as outlined by Kaur (2018), describe relationships between variables and organize data using measures of central tendency and variability. This study used the mean to assess data, categorizing averages as weak (1.00–2.33), moderate (2.34–3.67), and high (3.68–5.00). Descriptive analysis defined respondent profiles (e.g., gender, age, education) and organizational profiles (e.g., industry type, tenure, workforce size, ownership).

To assess if the data set was adequately simulated and to calculate the likelihood that the data for random variables will be regularly distributed, normality analysis is performed. Two popular tests for normalcy are the Shapiro Wilk and Kolmogorov-Smirnov tests. Since the study's sample size was less than fifty, Shapiro-Wilk was utilised; nevertheless, Kolmogorov-Smirnov was utilised because the sample size exceeded fifty.

Correlation analysis evaluates the relationship between a dependent variable (Overall Transportation System Performance) and an independent variable (Level of AI Prediction Model Utilization). Pearson correlation is used for normally distributed data, measuring linear relationships, but is sensitive to outliers. Spearman Rank correlation, suited for non-normal data, assigns ranks to values, with tied values receiving average ranks (Dudovskiy, 2018).

4. Results and Discussion

This study used SPSS Statistics Version 27.0 to analyse survey data through methods like data screening, pilot testing, reliability testing, normalcy testing, descriptive analysis, and Spearman correlation analysis. A pilot test with 30 respondents confirmed the questionnaire's validity. Out of 384 distributed questionnaires, 298 valid responses were collected, achieving a 77.61% response rate. A higher response rate improves data accuracy, aligning with the 60–80% target range suggested by Fincham (2008). These methods helped examine relationships between variables among young Malaysians.

4.2 Pilot Test

A pilot test with 30 respondents ensured the questionnaire was clear and reliable. After adjustments, the survey was distributed physically and via Google Forms, yielding 298 valid responses. The overall reliability statistics of the pilot test from 30 respondents are shown in Table 1. The reliability test included a total of 29 items. The number of items for the independent variables was Perception of Safety (7 items), Passenger Satisfaction (8 items), and the dependent variables were Adoption of AI in Public Transportation (8 items). The overall reliability test for two independent variables and one dependent variable was 0.876, as shown in Table 1, based on the results of the pre-test. Therefore, the reliability and validity test provided positive results.

Table 1 *Overall Reliability Statistics of Pilot Test*

Cronbach's Alpha	N of Items
0.876	23

4.3 Data Cleaning

Data cleaning is done after the data file has been imported into the SPSS program. To find any errors, inaccurate data entry, missing information, or outliers in the data gathering, this process was required. Consequently, the researcher can rectify or remove incomplete or erroneous data from the data collection process. There is no missing data in this study, as shown in Table 2.

Table 2 *Summary of Data Cleaning for Compute Variables of Value Analysis Process*

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Perception of Safety	298	100.0%	0	0.0%	298	100.0%
Passenger Satisfaction	298	100.0%	0	0.0%	298	100.0%
Adoption of AI in Public Transportation	298	100.0%	0	0.0%	298	100.0%

4.4 Descriptive Analysis

The items include gender, age, status of employment, and qualification. As illustrated in Table 3, majority were female (53.3%), 18 to 24 years old (40.6%), working (45.6%) and bachelor's degree (34.6%).

Table 3 *Demographic data*

Demographic	Detail	Frequency	Percent	Valid Percent	Cumulative Percent
Gender	Female	156	52.3	52.3	52.3
	Male	142	47.7	47.7	100.0
	Total	298	100.0	100.0	
Age	18-24	121	40.6	40.6	40.6
	25-34	55	18.5	18.5	59.1
	35-44	65	21.8	21.8	80.9
	45-54	38	12.8	12.8	93.6
	55 and above	11	3.7	3.7	97.3
	Under 18	8	2.7	2.7	100.0
	Total	298	100.0	100.0	
Status of Employment	Business	1	0.3	0.3	0.3
	E-hailing driver	1	0.3	0.3	0.7
	Housewife	13	4.4	4.4	5.0
	Not working	31	10.4	10.4	15.4
	Pensioner	14	4.7	4.7	20.1
	Student	101	33.9	33.9	54.0
	Working	1	0.3	0.3	54.4
	Working	136	45.6	45.6	100.0
	Total	298	100.0	100.0	
Qualification	Degree	103	34.6	34.6	34.6
	Diploma	62	20.8	20.8	55.4
	Master	16	5.4	5.4	60.7
	PhD	2	0.7	0.7	61.4
	Skills Certificate	35	11.7	11.7	73.2
	SPM	28	9.4	9.4	82.6
	STPM	52	17.4	17.4	100
	Total	298	100	100	

Table 4 presents the descriptive analysis of perception of safety, passenger satisfaction and adoption of AI in public transportation. Both independent variables, perception of safety and passenger satisfaction, show the same mean and standard deviation. deviation, which is 3.9367 and 0.68375. The dependent variable adoption of AI in public transportation shows 4.0872 for the mean and 0.69702 for the standard deviation. deviation.

Table 4 *Descriptive statistics of the level of the independent variable and the dependent variable*

	Mean	Std. Deviation
Independent Variable		
Perception of Safety	3.9367	0.68375

Passenger Satisfaction	3.9367	0.68375
Dependent Variable		
Adoption of AI in Public Transportation	4.0872	0.69702

4.5 Normality Test

The results of the normality test for independent and dependent variables are shown in Table 5. According to the data, all the variables, including perception of safety, passenger satisfaction, and adoption of ai in public transportation had the same significant value of 0.000. 34

Table 5 *Normality Test for Independent Variables and Dependent Variable*

Variables	Kolmogorov-Smirnova			Results
Dependent Variable	Statistic	df	Sig.	
Adoption of AI in Public Transportation	0.12	299	0.001	Not Normal
a. Lilliefors Significance Correction				

4.6 Spearman Correlation Coefficient

According to the statistics in Table 6, perception of safety has a correlation coefficient value of 0.644 ($\rho < 0.01$), and passenger satisfaction has a correlation coefficient value of 0.655 ($\rho < 0.01$). Based on this data, it can be concluded that there is a positive correlation between the two variables. Furthermore, perceived ease of use shows a stronger correlation than perceived usefulness. In short, increasing the independent variables' value would raise the dependent variable's value.

Table 6 *Strength of the relationship between independent and dependent variables*

Variables	Spearman Correlation Coefficient, ρ	Significant, p	Strength of Association
Perception of Safety	0.644	0.001	Strong positive correlation
Passenger Satisfaction	0.655	0.001	Strong positive correlation

The study found a strong positive correlation ($\rho = 0.644$, $p = 0.000$) between the perception of safety and AI adoption in public transportation, supporting H1 and rejecting H0. This aligns with prior research by Chen *et al*. (2021) and Abduljabbar, highlighting AI's role in enhancing transportation safety and managing complex systems. The study found a strong positive correlation ($\rho = 0.655$, $p = 0.000$) between passenger satisfaction and AI adoption in public transportation, supporting H2 and rejecting H0. This aligns with studies by Sony, Astya, and Bhushan, highlighting AI's role in improving system productivity, trip predictability, and transportation efficiency.

5. Conclusion

The study's first objective was to assess AI prediction models in transportation for risk assessment and safety improvement. Using SPSS for descriptive statistics, the mean and standard deviation of dependent variables were calculated. Results showed high mean scores of 3.9367 for both perception of safety and passenger satisfaction, indicating positive user attitudes in Klang Valley towards AI in public transportation. This aligns with findings by Abduljabbar (2019) and supports readiness for further investigation, achieving the study's first objective.

The study's second objective was to assess awareness of AI adoption in public transportation among Klang Valley residents. Using SPSS, the mean score of 4.0872 from descriptive statistics indicates a positive inclination toward AI, reflecting growing comfort and reliance on such advancements. This aligns with Rogers (2003) insights on adoption rates. The findings conclude that Malaysians generally have an agreed level of awareness, achieving the second research objective.

The third objective was to explore the relationship between perception of safety, passenger satisfaction, and AI adoption in public transportation. Using Pearson Correlation Coefficient, both factors showed strong positive correlations ($\rho = 0.655$). The findings align with prior research, such as studies by Huafeng Yu *et al*. (2004) and INIT, which highlight how AI enhances safety and passenger satisfaction through better route planning and real-time updates. These results confirm that higher safety perception and satisfaction increase the likelihood of AI adoption, achieving the third research objective.

In conclusion, AI-powered prediction models can enhance public transportation efficiency and safety, particularly in rapidly urbanising areas like Klang Valley. By improving traffic flow, route planning, and anticipating disruptions, AI can enhance the user experience. However, challenges like data accessibility, technology integration, stakeholder cooperation, and adapting to local conditions must be addressed for successful implementation. This study highlights the importance of integrating AI into public transit while addressing challenges like data gaps, resistance to change, and urban system complexity. Ensuring reliability, adoption, and addressing public trust, privacy, and equity concerns are essential for successful implementation. Continued research is crucial to optimize AI in public transit, focusing on improving data integration, developing adaptive models for urban settings, and addressing implementation challenges. Long-term studies will provide insights into the scalability and sustainability of AI solutions. AI-powered prediction models present a transformative opportunity for the Klang Valley's public transit system. Overcoming challenges and investing in further research can lead to a safer, more efficient, and user-friendly transport system for the growing population.

Acknowledgement

The authors would like to thank the Faculty of Technology Management and Business, Universiti Tun Hussein Onn Malaysia for its support.

Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Mohamad Amir Firdaus Zainuddin and Muhammad Ammar Shafi;* ***data collection:*** *Mohamad Amir Firdaus Zainuddin and Muhammad Ammar Shafi;* ***analysis and interpretation of results:*** *Mohamad Amir Firdaus Zainuddin and Muhammad Ammar Shafi;* ***draft manuscript preparation:*** *Mohamad Amir Firdaus Zainuddin and Muhammad Ammar Shafi. All authors reviewed the results and approved the final version of the manuscript.*

References

Abduljabbar, R. (2019). Applications of artificial intelligence in transport: An overview, MDPI. Available at: https://www.mdpi.com/2071-1050/11/1/189 (Accessed: 08 April 2024).

AI life safety image classification by using CNN architecture (2024). Perpustakaan Tunku Tun Aminah UTHM. Available at: https://help.oclc.org/Library_Management/EZproxy/Database_stanzas/EBSCO_Information_Services (Accessed: 11 April 2024).

Analysis of land transportation safety in the EU with respect to safety culture (2024). Perpustakaan Tunku Tun Aminah UTHM. Available at: https://help.oclc.org/Library_Management/EZproxy/Database_stanzas/EBSCO_Inform ation_Services (Accessed: 11 April 2024).

Artificial intelligence : a guide to intelligent systems / Michael Negnevitsky. (no date). Perpustakaan Tunku Tun Aminah UTHM. Available at: http://eds.a.ebscohost.com/ehost/detail?bdata=JnNpdGU9ZWhvc3QtbGl2ZSZzY29wZ T1zaXRl&hid=4205&sid=0bb66b78-6192-4474-8f4b5d2f514c41bb%40sessionmgr4001&vid=1 (Accessed: 12 April 2024).

Artificial intelligence : a new synthesis / Nils J. Nilsson. (no date). Perpustakaan Tunku Tun Aminah UTHM. Available at: http://eds.a.ebscohost.com/ehost/detail?bdata=JnNpdGU9ZWhvc3QtbGl2ZSZzY29wZ T1zaXRl&hid=4205&sid=0bb66b78-6192-4474-8f4b5d2f514c41bb%40sessionmgr4001&vid=1 (Accessed: 12 April 2024).

Artificial intelligence : approaches, tools, and applications / Brent M. Gordon, editor. (no date). Perpustakaan Tunku Tun Aminah UTHM. Available at: https://www.ebsco.com/ (Accessed: 12 April 2024).

Artificial intelligence : foundations of computational agents / David L. Poole, Alan K. Mackworth. (no date). Perpustakaan Tunku Tun Aminah UTHM. Available at: http://eds.a.ebscohost.com/ehost/detail?bdata=JnNpdGU9ZWhvc3QtbGl2ZSZzY29wZT1zaXRl&hid=4205 &sid=0bb66b78-6192-4474-8f4b5d2f514c41bb%40sessionmgr4001&vid=1 (Accessed: 12 April 2024).

Angel S. D. (2021) Infrastructure, mobility and Safety 4.0: Modernization in Road Transportation, *Technology in Society*. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0160791X21002669 (Accessed: 08 April 2024).

A Novel Cyber-Threat Awareness Framework based on Spatial-Temporal Transformer Encoder for Maritime Transportation Systems (2024). Perpustakaan Tunku Tun Aminah UTHM. Available at: https://help.oclc.org/Library_Management/EZproxy/Database_stanzas/EBSCO_Inform ation_Services (Accessed: 11 April 2024).

Claudine, B. (2020a). Self-driving cars: A survey, Expert Systems with Applications. Available at: https://www.sciencedirect.com/science/article/abs/pii/S095741742030628X (Accessed: 03 June 2024).

EBSCO Information Services (2024). OCLC Support. Available at: https://help.oclc.org/Library_Management/EZproxy/Database_stanzas/EBSCO_Inform ation_Services (Accessed: 11 April 2024).

Investigation of pedestrian and bicyclist safety in public transportation systems (2024). Perpustakaan Tunku Tun Aminah UTHM. Available at: https://help.oclc.org/Library_Management/EZproxy/Database_stanzas/EBSCO_Inform ation_Services (Accessed: 12 April 2024).

Ashokkumar, K. (2015). Cloud based Intelligent Transport System. *Procedia Computer Science*. Available at: https://www.sciencedirect.com/science/article/pii/S1877050915005621 (Accessed: 03 June 2024). Knowledge Translation for Improving Safety in Transportation (2024) Perpustakaan Tunku Tun Aminah UTHM. Available at: https://help.oclc.org/Library_Management/EZproxy/Database_stanzas/EBSCO_Inform ation_Services (Accessed: 11 April 2024).

Lakshmi, S., I. (2021). AI enabled applications towards Intelligent Transportation, *Transportation Engineering*. Available at: https://www.sciencedirect.com/science/article/pii/S2666691X21000397 (Accessed: 08 April 2024).

Passengers' Perceptions On Security And Safety In Public Transportation In 14 Ethiopia: A Case Study Of Addis Ababa, Perpustakaan Tunku Tun Aminah UTHM. Available at: https://www.ebsco.com/products/ebscohost-research-platform (Accessed: 12 April 2024).

Qiangqiang, G. (2019). Urban Traffic Signal Control with connected and automated vehicles: A survey, Transportation Research Part C: Emerging Technologies. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0968090X18311641 (Accessed: 03 June 2024).

Revolutionizing Transportation System Using Artificial Intelligence Technique (no date). Perpustakaan Tunku Tun Aminah UTHM. Available at: http://eds.b.ebscohost.com/ehost/detail?bdata=JnNpdGU9ZWhvc3QtbGl2ZSZzY29wZ T1zaXRl&hid=116&sid=27da8fff-a4f9-4947-b48b7c982bfb3222%40sessionmgr111&vid=1 (Accessed: 12 April 2024).

Tiago, Z. (2020). Predictive maintenance in the industry 4.0: A systematic literature review. *Computers & Industrial Engineering*. Available at: https://www.sciencedirect.com/science/article/abs/pii/S0360835220305787 (Accessed: 03 June 2024). (2021) Vision Meets Robotics: The kitti dataset - a Geiger, P Lenz, C Stiller, R urtasun, 2013. Available at: https://journals.sagepub.com/doi/full/10.1177/0278364913491297 (Accessed: 03 June 2024)