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Age-Based Awareness Disparities in Passenger Perception of Ai Cameras: A Study of Economic and Ethical Implications

Leena TU[1], Aswani P[2]

[1]Assistant Professor, Department of Commerce and Management, Government Arts and Science College, Chittur, Palakkad, Kerala, India.
[2]Master of Commerce, Department of Commerce and Management, Government Arts and Science College, Chittur, Palakkad, Kerala, India.

Abstract

The implementation of Artificial Intelligence into the surveillance system has remarkably transformed automated decision-making in the field of traffic and transportation systems. To ensure road safety, we have sought the services of Artificial Intelligence cameras, which have revolutionised the arena of traffic management. This article examines passengers' awareness and perception of AI cameras in automated traffic monitoring, with a specific focus on their economic, social, and ethical implications in the district of Palakkad. A descriptive and analytical approach to the research undertaken throws light on the effects of introducing AI cameras across various age groups.

Keywords: Artificial Intelligence cameras, road safety, traffic management, passengers' attitude.

INTRODUCTION

The integration of Artificial Intelligence into transportation systems marks a pivotal advancement in modern mobility, especially with the introduction of AI-powered cameras. These smart surveillance systems are designed to enhance safety, optimise traffic flow, and strengthen law enforcement. Acting as a core component of Intelligent Transportation Systems, Artificial Intelligence cameras utilise real-time data processing and machine learning to monitor road activities, identify violations, and support automated decision-making. They are not merely tools for image capture but are part of a broader system that includes computer vision, behavioural prediction, and intelligent traffic management.

Artificial intelligence cameras in transportation settings can recognise objects, analyse traffic density, detect violations, and monitor restricted zones. With the growing concerns around road safety and traffic congestion, especially in densely populated and rapidly urbanising regions, these technologies offer promising solutions. In India, particularly in the state of Kerala, authorities have initiated widespread use of Artificial Intelligence surveillance cameras to monitor traffic violations and enforce road safety rules. This study examines the attitude of passengers towards AI cameras in the traffic infrastructure in the district of Palakkad in Kerala state, with a specific focus on its social and economic implications. Palakkad district, as a significant transit point and gateway to Kerala, has witnessed the deployment of these technologies in recent times.

While Artificial intelligence camera systems contribute to accident reduction and improved regulatory enforcement, their implementation has sparked varied public reactions. On the one hand, passengers appreciate enhanced safety and orderly road conduct; on the other, concerns about data privacy, increased financial burden through fines, and lack of awareness persist. Moreover, economic implications such as penalty costs and maintenance expenses may affect public perception, especially among frequent commuters and low-income passengers.

Understanding passengers' attitudes towards Artificial intelligence cameras is crucial to gauging the social acceptance and long-term viability of such interventions. Public cooperation plays a significant role in determining the success of technological adoption in public domains. Therefore, analysing awareness levels, perceived benefits and drawbacks, ethical concerns, and financial implications becomes critical for policymakers, traffic authorities, and urban planners.

The existing literature highlights a growing body of research focused on the integration of Artificial Intelligence in transportation systems, particularly emphasising Artificial Intelligence cameras for surveillance, safety, and traffic management. Several studies have underscored the technical and operational benefits of Artificial intelligence, including improved pedestrian safety (Kim J, 2021), traffic flow optimisation (Zhan X, 2019), and enhanced urban mobility (Gupta R, 2019).

In the context of India, Thomas (2023) emphasised the role of public awareness and regional differences in AI adoption, particularly noting resistance in rural areas like Palakkad. Jasmin (2023) and Asawari (2018) provided broader reviews on the global application of Artificial intelligence in transport, including the challenges and potential for urban transformation.

Other studies have concentrated on specific applications such as vehicle recognition using deep learning (Garcia M, 2021), Artificial intelligence surveillance for road safety (Hernandez C, 2020), and the integration of Artificial intelligence cameras with autonomous vehicles (Park YS, 2020). These works establish the technical efficiency and safety benefits of AI, while also highlighting concerns about data privacy, ethical surveillance, and economic implications.

However, a clear research gap exists in understanding **passengers' attitudes and economic concerns**, particularly in semi-urban Indian regions. Most studies have focused on technological effectiveness rather than public perception and acceptance. This underscores the need for localised research, such as the present study, which investigates how AI cameras are perceived by passengers in Palakkad district, considering both their benefits and drawbacks.

This research aims to explore passengers' awareness and perceptions of Artificial intelligence cameras in Palakkad district, investigate the economic impact on commuters, and evaluate the challenges and ethical considerations associated with their implementation. By studying these factors, the research contributes to the broader discourse on human-centred AI adoption and helps shape future transportation policies grounded in public trust and economic fairness.

METHODOLOGY

The methodology of this study is designed to systematically examine and analyse the attitudes of passengers towards AI cameras in transportation, with a specific focus on the economic implications in the Palakkad district of Kerala. This section outlines the research design, sources of data, sampling method, tools of analysis, and the period of study, which collectively form the foundation for achieving the research objectives.

Research Design

The research follows a descriptive and analytical design. Descriptive research enables the researcher to provide a clear picture of the respondents' awareness, opinions, and concerns related to Artificial intelligence cameras. Analytical methods are used to interpret the data and draw meaningful insights, particularly about how passengers perceive the economic and ethical aspects of this surveillance technology. The study does not aim to manipulate any variables but seeks to understand naturally occurring patterns in passenger behaviour and attitudes.

Sources of Data

To develop a comprehensive understanding of public attitudes toward AI camera implementation in transportation, the study utilised both **primary and secondary data sources**. **Primary data** was obtained directly from passengers through a structured questionnaire designed to capture various dimensions, including awareness, perceived benefits, economic burden, and privacy concerns. The questionnaire included both closed-ended and open-ended questions to ensure the collection of both **quantitative and qualitative insights**. In addition, **secondary data** were drawn from existing literature such as journal articles, government publications, newspaper reports, and credible online sources. These materials helped establish the study's background and offered valuable context regarding the implementation and impact of Artificial Intelligence cameras in Kerala and other regions.

Population and Sampling

The study focused on passengers in the Palakkad district, including those using personal, public, or commercial transport. Due to time and resource constraints, convenient sampling was used to select 100 respondents who were easily accessible and willing to participate. While this non-probability method may not fully represent the broader population, it enabled efficient data collection. The sample included individuals from various age groups, genders, and occupations to capture diverse perspectives on the issue.

Tools of Analysis

The data collected through the questionnaire were analysed using Two-Way ANOVA. This statistical tool helps identify whether there is any significant interaction between two independent variables on a dependent variable. It is particularly useful in understanding how demographic factors and behavioural variables influence passenger perceptions, enabling the researcher to identify key determinants in shaping public opinion on AI surveillance in transportation.

Period of the Study

The study was conducted over a period of 21 days, allowing sufficient time for the distribution and collection of questionnaires, data compilation, and statistical analysis. This time frame was adequate for reaching the target sample size and conducting a preliminary but insightful exploration of the research topic.

ANALYSIS AND DISCUSSIONS

This study investigates passengers' attitudes toward AI cameras in transportation, focusing on awareness, economic concerns, and ethical perceptions. Using descriptive statistics and Two-Way ANOVA, it examines key areas such as AI system awareness, financial impacts like fines, and concerns over privacy and data security. The sample is predominantly young (62% under 25) and female (71%), with most respondents being students (62%) and low-income earners (61% earning below ₹10,000). Respondents live across rural (45%), urban (40%), and sub-rural (15%) areas. Two-wheelers are the primary mode of transport (53%), with daily travel (76%) largely for education (39%) and work (35%). These insights offer a comprehensive understanding to guide future AI policy and implementation in transportation.

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AWARENESS OF RULES AND REGULATIONS

Table 1 Age-wise estimated marginal means – awareness of rules and regulations

Age	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Below 25	4.148	.111	3.928	4.368
25-35	4.087	.210	3.671	4.503
36-45	4.025	.227	3.574	4.476
Above 45	4.641	.194	4.257	5.026

Table 1 indicates that awareness of AI camera rules and regulations is highest among passengers aged above 45 (mean = 4.641), followed by those below 25 (mean = 4.148). The 25–35 and 36–45 age groups show slightly lower awareness levels, with means of 4.087 and 4.025, respectively.

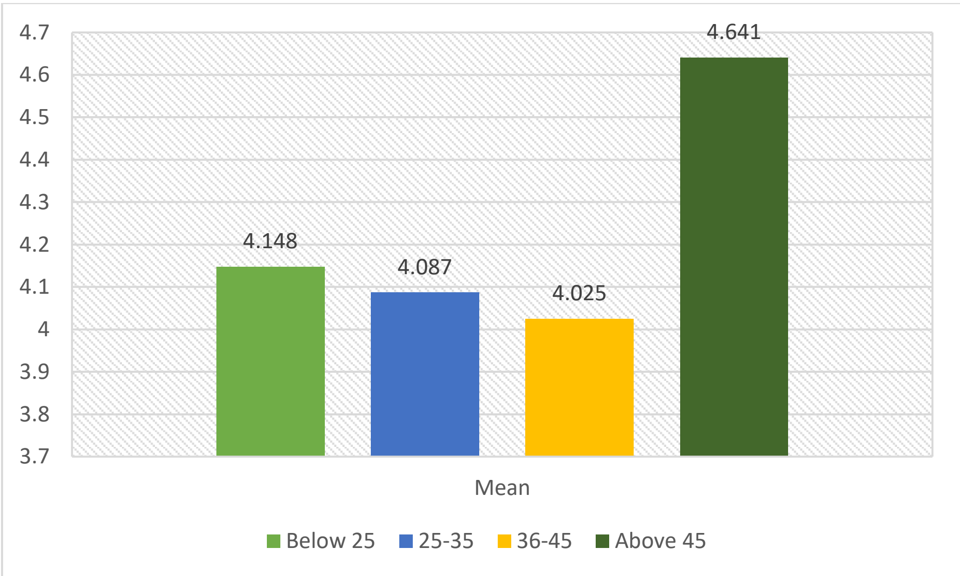

Figure 1: Age-wise estimated marginal means – awareness of rules and regulations

Table 2 Gender wise estimated marginal means – awareness of rules and regulations

Gender	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Male	4.295	.144	4.010	4.580
Female	4.156	.118	3.921	4.391

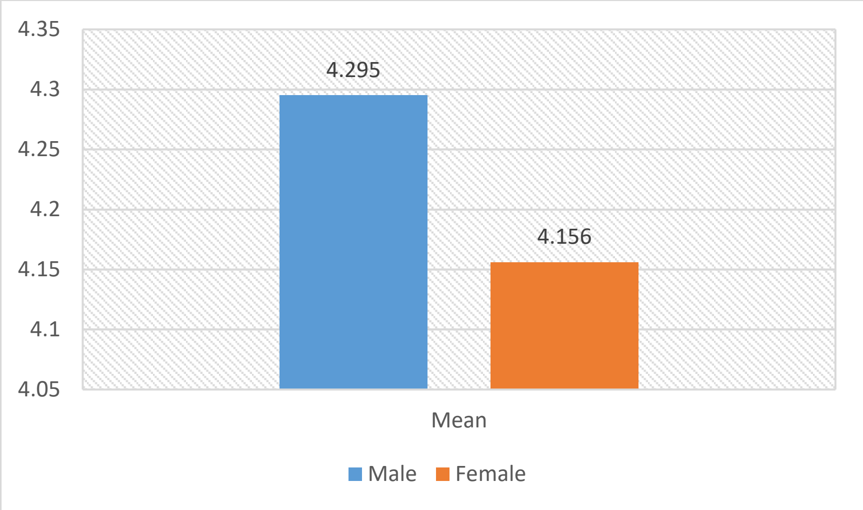

Figure 2 Gender wise estimated marginal means – awareness of rules and regulations

Table 3 Two-Way ANOVA

Source	Type I Sum Of Squares	Df	Mean Square	F	Sig.
Age	1745.660	4	436.415	844.195	.000***
Gender	.292	1	.292	.564	.454
Error	49.111	95	.517		
Total	1795.063	100			

The Two-Way ANOVA table shows that age has a statistically significant effect on the awareness and understanding of Artificial Intelligence camera rules and regulations (F = 844.195, p = .000), as indicated by the triple asterisk (***), confirming significance at the 5% level. In contrast, gender does not have a significant effect (F = 0.564, p = .454), suggesting that awareness levels do not vary notably between males and females. Therefore, differences in awareness are influenced more by age than by gender.

AWARENESS OF PROCEDURES AND MECHANISMS

Table 4 Age-wise estimated marginal means – awareness of procedures and mechanisms

Age	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Below 25	3.745	.134	3.478	4.012
25-35	3.591	.254	3.087	4.095
36-45	3.625	.276	3.078	4.172
Above 45	3.704	.235	3.238	4.171

Table 4 shows that awareness of procedures and mechanisms is relatively consistent across age groups, with the highest mean score observed in the below-25 group (3.745), indicating slightly greater awareness among younger participants. Older age groups, particularly those between 25–45, show more variability in responses, as reflected in their wider confidence intervals.

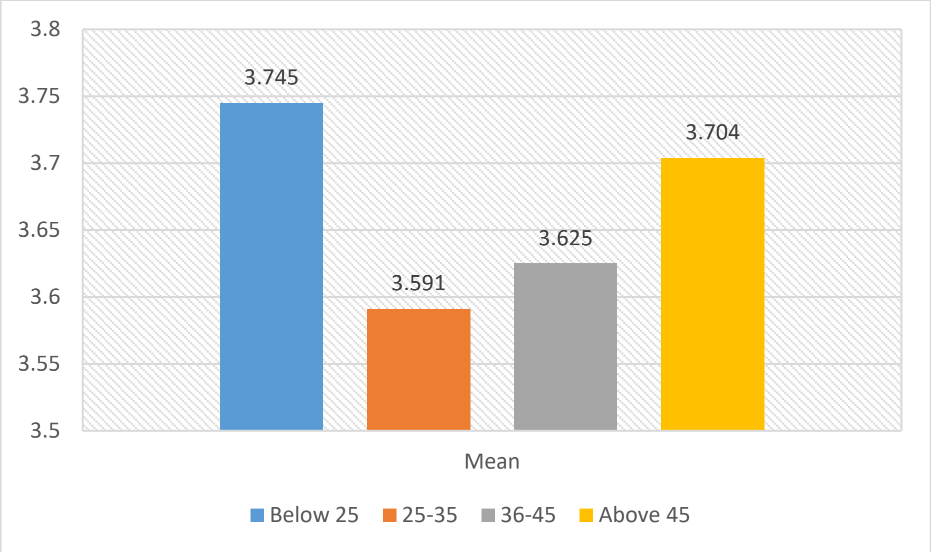

Figure 3 Age-wise estimated marginal means – awareness of procedures and mechanisms

Table 5 Gender wise estimated marginal means- awareness of procedures and mechanisms

Gender	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Male	3.909	.174	3.563	4.255
Female	3.424	.143	3.139	3.708

Table 5 indicates that males (mean = 3.909) have a higher awareness of procedures and mechanisms compared to females (mean = 3.424). The confidence interval for males (3.563–4.255) is also slightly wider than that for females (3.139–3.708), suggesting greater variability among male responses.

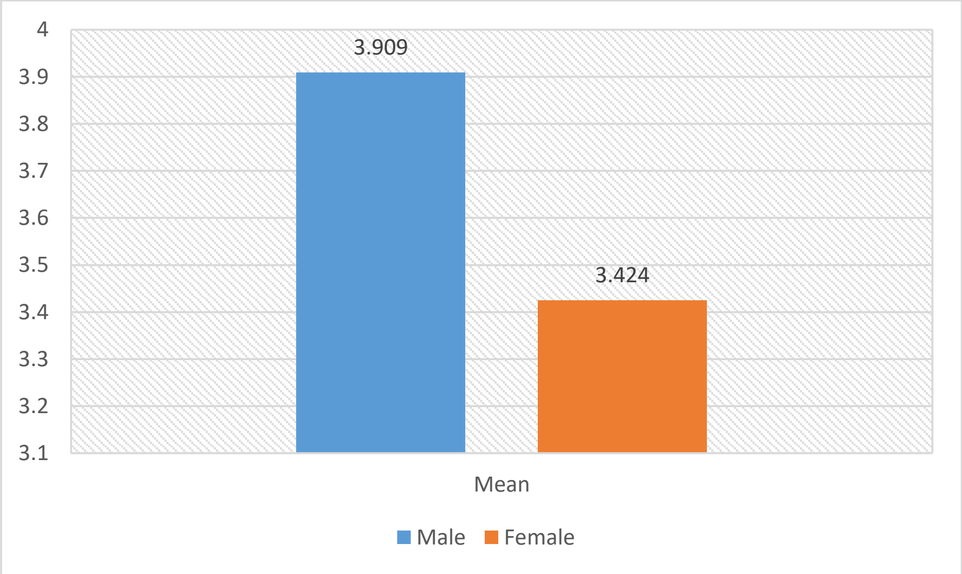

Figure 4 Gender wise estimated marginal means- awareness of procedures and mechanisms

Table 6 Two-way ANOVA Tests of Between-Subjects Effects

Source	Type I Sum Of Squares	Df	Mean Square	F	Sig.
Age	1300.974	4	325.243	428.424	.000***
Gender	3.531	1	3.531	4.651	.034*
Error	72.120	95	.759		
Total	1376.625	100			

***Significant at 5 per cent**

The mean variation of the scores for awareness of procedures and mechanisms among Below 25, 25- 35, 36-45, Above 45 and male and female is tested by two way ANOVA, which shows that Gender wise variation of the mean scores is statistically significant at 5 percent level of significance (value of F 4.651 df with 1 and $p=0.034<0.05$) also age wise variation of the mean score is statistically significant at 5 percent level of significance.

AWARENESS OF GOVERNMENT INTERVENTION

Table 6 Mean Scores of Awareness of Government Intervention Based on Age Group

Age	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Below 25	3.644	.135	3.375	3.912
25-35	3.765	.256	3.258	4.272
36-45	3.275	.277	2.724	3.826
Above 45	3.454	.236	2.984	3.923

The table presents the mean scores and confidence intervals for awareness of government intervention across different age groups. Individuals aged 25–35 have the highest mean score of 3.765, indicating a relatively greater awareness of government intervention compared to other age groups. This is followed by those below 25 years (mean = 3.644) and above 45 years (mean = 3.454). The lowest mean awareness is observed in the 36–45 age group (mean = 3.275).

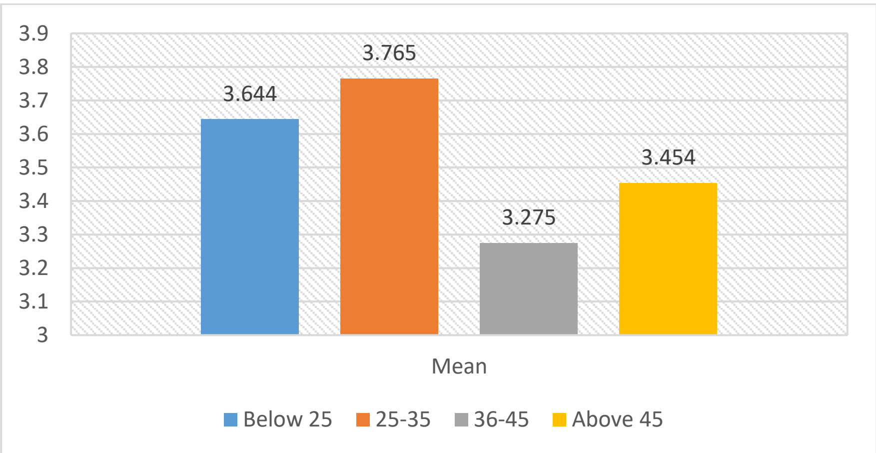

Figure 5: Mean Scores of Awareness of Government Intervention Based on Age Group

Table 7 Gender wise estimated marginal means awareness of government intervention

Gender	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Male	3.723	.175	3.375	4.071
Female	3.346	.144	3.059	3.633

Table 7 shows that males (Mean = 3.723) have a higher estimated marginal mean score for awareness of government intervention compared to females (Mean = 3.346), indicating that male respondents are relatively more aware of government actions.

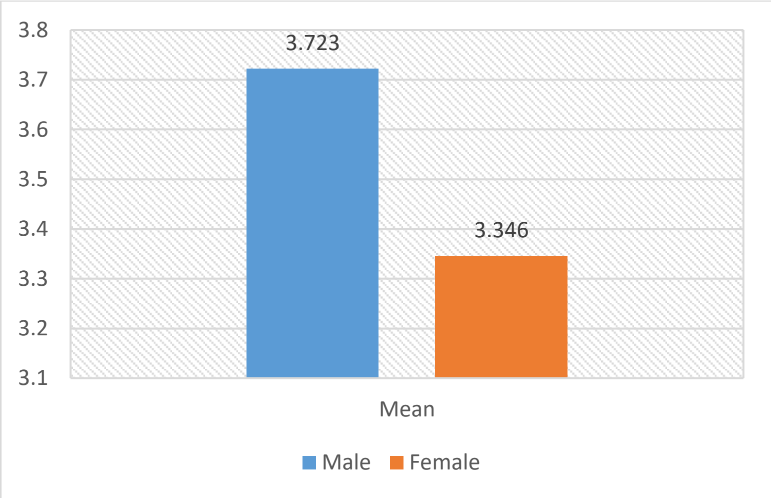

Table 6 Gender wise estimated marginal means awareness of government intervention

Table 8: Two-way ANOVA Awareness of Government Intervention

Source	Type I Sum Of Squares	df	Mean Square	F	Sig.
Age	1236.325	4	309.081	401.962	.000***
Gender	2.127	1	2.127	2.766	.100
Error	73.048	95	.769		
Total	1311.500	100			

The mean variation of the scores for awareness of procedures and mechanisms among Below 25, 25- 35, 36-45, Above 45 and male and female is tested by two way ANOVA, which shows that Gender wise variation of the mean scores is not statistically significant at 5 percent level of significance (value of F 2.766 df with 1 and p=0.100>0.05) but age wise variation of the mean score is statistically significant at 5 percent level of significance (value of F 401.962 df wit 4 and p=0.00>0.05).

DISCUSSION ON FINDINGS

The analysis of respondents' attitudes toward Artificial Intelligence (AI) cameras in transportation reveals several key patterns shaped by demographic variables such as age and gender. Notably, awareness of rules and regulations related to AI cameras shows a clear age-based variation. Older individuals (above 45) exhibit the highest awareness levels (Mean = 4.641), possibly due to longer driving experience and exposure to formal regulations. Interestingly, younger respondents (below 25) also demonstrate relatively high awareness, suggesting that digital literacy and exposure to media may play a role in familiarising them with AI enforcement tools. The Two-Way ANOVA confirms that age significantly influences awareness ($p = .000$), while gender does not, indicating that educational or informational efforts may be more effective if tailored by age rather than gender.

In terms of awareness of procedures and mechanisms surrounding AI camera implementation, the data again indicates that younger individuals (especially those below 25) report slightly higher mean scores, though the differences across age groups are less pronounced than for rule awareness. However, gender differences here are more evident, with males showing significantly greater awareness than females (Mean = 3.909 vs. 3.424). The ANOVA supports this finding, showing a statistically significant gender effect ($p = .034$), as well as an age effect ($p = .000$). This may reflect differing levels of interest or exposure to technology-related processes between genders, suggesting a need for more inclusive communication strategies.

The third area explored is awareness of government intervention in transportation safety through AI technology. Respondents aged 25–35 exhibit the highest mean score (3.765), suggesting that young working professionals may be more attuned to or affected by AI enforcement mechanisms, possibly due to their active road usage and financial liability for fines. Conversely, individuals aged 36–45 show the lowest awareness (Mean = 3.275), which may point to gaps in communication or engagement in that demographic. While male respondents again show higher awareness than females, the gender difference is not statistically significant ($p = .100$), reaffirming that age plays a more critical role in shaping awareness in this area as well ($p = .000$).

These findings indicate that age is a consistent and significant factor affecting awareness across all dimensions studied—rules and regulations, procedures and mechanisms, and government intervention—while gender plays a more nuanced role, influencing awareness of procedures but not the other two areas. These insights can guide targeted outreach and education efforts, particularly focusing on middle-aged groups and improving accessibility of procedural knowledge for female road users. Understanding these demographic dynamics is essential for fostering public acceptance and effective implementation of AI technologies in transportation.

CONCLUSION

This study highlights that age plays a critical role in shaping public awareness of artificial intelligence cameras in transportation. Awareness levels regarding rules, operational procedures, and government interventions vary significantly across age groups, underscoring the need for age-specific educational and awareness strategies.

Participants above 45 years exhibit the highest awareness of traffic rules and regulations, likely due to their extensive driving experience and long-term exposure to traditional enforcement systems. Their familiarity with conventional road safety practices contributes to this elevated understanding.

In contrast, young adults aged 25–35 show the highest awareness of government interventions. This may stem from their frequent commuting for professional purposes and their greater exposure to traffic fines and digital monitoring systems. Their active engagement with news and governance issues also enhances their awareness.

Respondents under 25 years demonstrate slightly higher awareness of the procedural and technical aspects of artificial intelligence enforcement. Their comfort with digital tools and frequent interaction with technology contribute to their greater understanding and acceptance of artificial intelligence-based systems.

While gender differences in overall awareness are not statistically significant, male respondents display slightly higher awareness of procedural mechanisms. This may reflect variations in driving behaviour, exposure to enforcement procedures, or interest in technology.

The 36–45 age group consistently shows the lowest awareness levels across all dimensions. This gap may be due to limited engagement with both traditional media and newer digital platforms, pointing to a need for more targeted outreach to this demographic.

These findings suggest that awareness initiatives should be tailored to the specific needs of each age group. Digital channels are well-suited for reaching younger audiences, while in-person community programs or conventional media may be more effective for older or less digitally engaged individuals.

Though gender disparities are minimal, efforts should be made to improve procedural awareness among female respondents. Simplifying technical content and sharing it through familiar, widely used platforms can help bridge this gap.

The high levels of awareness among youth and students confirm the effectiveness of digital and educational outreach. This reinforces the importance of integrating AI and road safety topics into academic curricula and online awareness campaigns.

Policy makers and stakeholders should adopt demographically informed strategies for public communication. Recognising and addressing the distinct awareness patterns across age and gender will help enhance compliance, promote road safety, and support the successful implementation of artificial intelligence.

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