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Assessing the Role of Human Factors in Traffic Accident Causation

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ABSTRACT

This study investigates the influence of driver behavior and demographic characteristics on the frequency of traffic accidents in Al-Anbar Governorate, Iraq. A structured survey was administered to a representative sample of 900 licensed drivers, capturing behavioral and demographic factors associated with accident risk. Data analysis was performed using both multiple linear regression and ordinal logistic regression equations. The linear regression equation demonstrated excellent explanatory power (Adjusted $R^2 = 0.984$), identifying key predictors such as age, driving experience, speeding, sudden braking, and mobile phone use while driving. The ordinal logistic regression confirmed these findings (Nagelkerke $R^2 = 0.944$) and further highlighted intentional obstruction, driving against traffic, and chasing other vehicles as significant contributors to accident frequency and severity. Conversely, behaviors such as using turn signals, abrupt lane shifts, and slow driving on the left were not statistically significant. These findings underscore the need for targeted enforcement, public awareness campaigns, and behavior-focused interventions to mitigate high-risk actions and improve road safety. The results offer evidence-based insights to support traffic safety policymaking in regions facing similar challenges.

1. INTRODUCTION

Driver behavior plays a critical role in shaping road safety outcomes. Globally, road traffic injuries remain a major public health concern, causing approximately 1.3 million deaths annually and imposing significant economic and social burdens. Numerous studies have consistently demonstrated a strong association between human behavioral factors—such as distraction (e.g., mobile phone use), aggression, sudden braking, or tailgating—and an increased risk of traffic accidents.

This study focuses on examining driver behaviors in Al-Anbar Governorate, Iraq. A structured questionnaire was distributed to a diverse sample of 900 drivers to collect data on demographic and behavioral variables potentially linked to accident frequency. Specifically, the study analyzed a total of 20 factors—covering both demographic characteristics and behavioral patterns—which have not been collectively examined in previous Iraqi studies. In fact, such research remains scarce in Iraq, highlighting the novelty and importance of the present investigation.

Key factors such as vehicle ownership, occupation, and specific driving practices were analyzed to determine their relationship to accident involvement. Statistical tools—including multiple linear regression and ordinal logistic regression—were employed to identify high-risk behaviors and assess their significance. The findings aim to inform the development of targeted interventions to reduce risky driving habits and support the formulation of data-driven road safety policies.

Moreover, the study contributes to the existing literature by offering localized insights into driver behavior patterns, while proposing strategies for awareness campaigns and regulatory reforms to reduce accident rates and enhance traffic safety.

Several international studies have examined the role of behavioral factors in road safety. In the United States, the behaviors and attitudes of 680 young drivers from Central Florida were analyzed using structural equation modeling [1]. The study identified aggressive driving and distractions as key risk factors among the 16–17 age group, while older adolescents (18–24) were more influenced by favorable attitudes toward speeding and in-vehicle distractions. Targeted interventions addressing time urgency and peer influence were recommended to reduce violations among young drivers [2].

Another U.S.-based study investigated self-identified aggressive drivers and found them to be less concerned about risky behaviors such as speeding and phone use, while also reporting higher rates of alcohol-related driving [3]. The authors emphasized the need for strict law enforcement and public awareness campaigns to curb aggressive driving.

In France, a study examined the link between Type A behavior—characterized by impatience, hostility, and urgency—and road accident risk [4]. Using data from the GAZEL cohort, individuals with high Type A scores exhibited a 40% increased likelihood of severe accidents, highlighting the influence of personality traits on driving safety [5].

In Germany, researchers developed a behavioral profiling method for use in multi-agent traffic simulations [6]. Drivers were categorized based on patterns such as lane keeping, overtaking, and speed preferences. These profiles improved simulation accuracy and contributed to more precise traffic safety assessments.

In Japan, a study of 373 drivers under potentially hazardous conditions identified braking patterns and verbal reactions as indicators of perceived danger [7]. The multimodal analysis demonstrated predictive value for real-time driver monitoring systems.

In China, researchers introduced the Traffic Order Index (TOI) to assess aggressive driving at urban interchange exits using data from navigation applications [8]. They found that both road conditions and device usage significantly influenced driving safety, prompting recommendations for improved signage and infrastructure.

A separate Chinese study used driving simulators to examine post-congestion behavior [9]. It found that drivers exhibited increased aggression and decreased situational awareness immediately after exiting congested areas. The findings support the implementation of targeted safety education.

In Kuwait, research on university students' traffic attitudes revealed that, despite awareness of driving rules, many young drivers engaged in risky behaviors such as speeding [10]. The study emphasized the importance of education and graduated licensing systems to enhance safety among youth.

In the United Arab Emirates, GIS analysis was employed to examine driver behavior and identify accident hotspots in Abu Dhabi [11]. Careless driving, particularly among middle-aged drivers, was a leading cause of accidents. The study advocated for interventions targeting both behavioral and location-specific risks.

In Saudi Arabia, a study in Hail Province attributed 60% of accidents to human error, with speeding and failure to follow traffic rules being the primary causes [12]. The researchers recommended enhanced enforcement and public awareness to address these issues.

In North Cyprus, a two-phase methodology integrating surveys and accident records was used to identify key accident causes [13]. Human and road-related factors, especially negligent driving and speeding, were found to be the main contributors. Policy measures addressing driver behavior and infrastructure were proposed.

In Iran, cluster analysis was applied to classify drivers into groups ranging from safe and experienced to high-risk and aggressive [14]. This classification enabled targeted interventions for improving road safety among high-risk groups.

Another Iranian study examined the association between aberrant driving behaviors and traffic accidents [15]. It identified unintentional speeding, overtaking, and distraction as major predictors of harm, with socio-demographic variables like age and gender also playing a role.

In India, a review of behavioral factors contributing to accidents found strong links with speeding, mobile phone use, fatigue, aggression, and substance abuse [16]. The study recommended behavioral change models, such as the Health Belief Model, to guide intervention strategies.

A comprehensive review of inattention detection technologies explored the effectiveness of both visual and non-visual systems, highlighting recent advancements in mobile and wearable tech [17]. The integration of these systems into vehicle-to-vehicle communication networks was proposed to enhance real-time road safety.

Driving simulator experiments also revealed that real-time driver assistance systems improved behaviors, such as reaction times and safe lane changes [18]. The results demonstrated the potential of connected vehicle technologies to reduce accident risk.

Research into the impact of driver typology on traffic flow characteristics showed that aggressive drivers increased flow but reduced overall stability [19]. The study recommended public education campaigns to improve safety and efficiency.

In Ghana, a study examined the link between organizational safety climate and risky driving among corporate drivers [20]. Younger drivers were more prone to dangerous behaviors, but a strong safety culture within organizations significantly reduced these tendencies. The findings support the development of safety-focused workplace policies to prevent work-related road accidents.

2. METHODOLOGY

This study employed a quantitative cross-sectional design to investigate the effect of driver behavior on traffic safety in Al-Anbar Governorate. Data were collected through a structured survey distributed to 900 drivers across various cities and districts in the province. The sample was predominantly male and included a wide age range and occupational diversity, such as students, government employees, and private-sector workers.

The questionnaire focused on 20 behavioral variables (e.g., speeding, mobile phone use, sudden braking) and key demographic factors (e.g., age, sex, occupation, vehicle ownership). After data cleaning and preparation, analysis was conducted using SPSS.

The statistical analysis included:

- **Multiple Linear Regression** to examine the relationship between driver behaviors and the continuous outcome (number of accidents),
- **Ordinal Logistic Regression**, an advanced statistical technique suitable for modeling an ordinal dependent variable (categorized number of accidents into four severity levels).

These two regression methods provided complementary insights into how individual behaviors and demographics contribute to accident risk, both in frequency and severity. Tests for normality (skewness, kurtosis, and histograms) and multicollinearity checks were also conducted to ensure equation validity.

Ethical approval was obtained from relevant academic and local authorities. All participants gave informed consent, and data were collected anonymously to ensure privacy and candid responses.

3. RESULTS AND DATA ANALYSIS

3.1 Descriptive statistics

The demographic distribution of the sample is presented in Table 1. The majority of participants were male (94.7%), and the age groups were equally represented, each comprising 16.7% of the total. Regarding vehicle ownership, more than half of the participants (56.7%) owned private vehicles, while the remaining 43.3% reported driving family-owned vehicles. This balanced demographic structure supports the reliability of the statistical comparisons performed in the study.

Table 1. Demographic factors of participants

Parameter	Classification	The Percentage
SEX	Male	94.70%
	Female	5.30%
AGE	18-26	16.7 %
	27-35	16.7 %
	36-44	16.7 %
	45-53	16.7 %
	54-62	16.7 %
	63-71	16.7 %
Vehicle Ownership	Private	56.70%
	Family	43.30%

Table 2 presents the descriptive statistics analysed using SPSS. These statistics include the following variables: Number of participants (N), Standard Deviation, Skewness, and Kurtosis. These measures help evaluate the data distribution for each variable and understand its fundamental characteristics.

- Number of Participants (N): Indicates the number of observations processed for each variable.
- Standard Deviation: Measures the data's degree of dispersion or variability. Low values (close to zero) indicate that the data points are tightly clustered around the mean, signifying minimal variation. Conversely, higher values reflect greater dispersion in the data.
- Skewness: Assesses the asymmetry of the data distribution. Values close to 0 suggest a nearly symmetrical distribution. Positive skewness indicates that the data are skewed toward smaller values (left tail), while negative skewness implies skewness toward larger values (right tail).
- Kurtosis: Evaluates the degree of flatness or peakedness in the data distribution compared to a normal distribution. Values near 0 suggest a normal distribution. Negative kurtosis indicates a flat distribution (spread out and less concentrated), while positive kurtosis reflects a peaked distribution (more concentrated around the mean).

The results reveal that most studied variables exhibit low to moderate standard deviation, indicating that the data are generally clustered around the mean with minimal dispersion. Among the variables, "Using a mobile phone while driving" showed the highest standard deviation (1.207), suggesting greater variability in responses, while "Respond when you are passed" had the lowest standard deviation (0.663), indicating more consistent responses. In terms of skewness, which measures the asymmetry of the data distribution, "Speaking loudly when provoked" displayed the highest positive skewness (0.110), implying a slight tendency toward lower scores, while "Passing from the right" had the most negative skewness (-0.063), suggesting a minor lean toward higher scores. Regarding kurtosis, which reflects the peakedness or flatness of the distribution, "The number of accidents" exhibited the most negative kurtosis (-0.879), indicating a relatively flat distribution with lighter tails, whereas "Use the signal when changing sides" had the least negative kurtosis (-0.515), showing a distribution that is slightly less flat. These statistical properties demonstrate that the dataset possesses appropriate characteristics for further analysis, such as regression equation and hypothesis testing, thereby reinforcing the credibility and reliability of the study's findings.

3.2 Linear regression analysis and significant predictors

A p-value is a statistical metric employed to determine the significance of results obtained in hypothesis testing. It indicates the probability of observing the results, assuming the null hypothesis is true. A diminutive p-value, significantly less than 0.05, provides strong evidence against the null hypothesis, indicating a statistically significant relationship. The regression analysis revealed essential insights into the role of demographic and behavioral factors in influencing traffic accident risk (Table 3). Demographic variables such as age, years of driving experience, and place of work or study demonstrated high statistical significance ($p < 0.001$), highlighting their strong association with accident likelihood. Additionally, driving outside the speed limit, sudden braking, responding when overtaken, passing from the right ($p = 0.005$), and notably, using a mobile phone while driving ($p = 0.012$), were all found to significantly impact accident frequency.

On the other hand, several behaviors—including speaking loudly when provoked ($p = 0.929$), chasing another vehicle ($p = 0.634$), intentional obstruction ($p = 0.602$), and slow driving on the left side ($p = 0.566$)—did not exhibit statistically significant effects. These findings underscore the importance of focusing safety interventions and awareness campaigns on the most impactful behaviors to effectively reduce accident rates and enhance traffic safety outcomes.

Table 2. Descriptive statistics

N Statistic		Std. Deviation Statistic	Skewness		Kurtosis	
			Statistic	Std. Error	Statistic	Std. Error
Driving outside the speed limit	900	1.171	-0.022	0.082	-0.698	0.163
Using a mobile phone while driving	900	1.207	0.065	0.082	-0.719	0.163
Intentional obstruction	900	1.137	0.042	0.082	-0.586	0.163
Chasing a vehicle	900	1.140	0.059	0.082	-0.606	0.163
Sudden braking	900	1.137	0.028	0.082	-0.591	0.163
Driving against traffic	900	1.176	0.014	0.082	-0.713	0.163
Use the signal when changing sides	900	1.109	-0.050	0.082	-0.515	0.163
Speaking loudly when provoked	900	1.144	0.110	0.082	-0.581	0.163
Shift the path from the far right to the far left	900	1.149	0.009	0.082	-0.591	0.163
Passing from the right	900	1.119	-0.063	0.082	-0.531	0.163
Slow driving on the Left Side	900	1.147	0.033	0.082	-0.559	0.163
Respond when you are passed	900	0.663	0.032	0.082	-0.722	0.163
Parking the car on the traffic lanes	900	1.174	-0.029	0.082	-0.649	0.163
The number of accidents	900	0.937	0.037	0.082	-0.879	0.163
Valid N (listwise)	900					

Table 3. P-values of demographic and behavioral variables from the linear regression equation

Variable	P-Value
Demographic Factors	
Sex	0.003
Age	P < 0.001
Vehicle ownership	0.154
Occupation	0.019
Place of work or study	P < 0.001
Years of driving experience	P < 0.001
Driving Behaviors	
Driving outside the speed limit	P < 0.001
Using a mobile phone while driving	0.012
Intentional obstruction	0.602
Chasing a vehicle	0.634
Sudden braking	P < 0.001
Driving against traffic	0.289
Use the signal when changing sides	0.424
Speaking loudly when provoked	0.929
Shift the path from the far right to the far left	0.260
Passing from the right	0.005
Slow driving on the Left Side	0.566
Respond when you are passed	P < 0.001
Parking the car on the traffic lanes	0.091

Note: All p-values less than 0.001 are reported as "p < 0.001" in accordance with standard statistical reporting guidelines.

3.3 Model fit and statistical indicators

In addition to analysing individual variables and driving behaviours associated with traffic accident rates, key statistical indicators were used to assess the overall strength and reliability of the linear regression equation. As shown in Table 4, the Adjusted R-squared value was 0.984, indicating that approximately 98.4% of the variance in the dependent variable (number of accidents) is explained by the model—reflecting excellent explanatory power. The F-statistic value (6970.79) further confirms the statistical significance of the model, while the low Mean Squared Error (MSE = 0.0014) indicates high prediction accuracy. Collectively, these indicators support the robustness of the model and the reliability of the identified predictors in explaining traffic accident frequency.

To assess the impact of demographic and behavioral variables on the frequency of traffic accidents, an ordinal logistic regression analysis was conducted. This method was appropriate as the dependent variable—the number of traffic accidents—is ordinal in nature with four ordered categories. The regression estimates provide insights into how each independent variable contributes to the likelihood of falling into higher or lower accident frequency categories, controlling for other factors in the model.

Table 4. Model strength and statistical indicators

R-Squared:	0.9842
Adjusted R-Squared:	0.9842
Std. The error of the Estimate:	0.038836683824539905
F-Statistic:	F-Statistic: 6970.792184

The estimated coefficients and their statistical significance are presented in Table 5. A negative coefficient indicates that an increase in the predictor is associated with a lower probability of being in a higher accident category, while a positive coefficient suggests an increased probability. Several behavioral variables demonstrated statistically significant effects. Notably, "Driving outside the speed limit" (Estimate = -73.103, p = 0.044) and "Driving against traffic" (Estimate = -72.906, p < 0.001) were strongly associated with higher accident frequencies, highlighting their critical role in accident causation. Additionally, "Intentional obstruction" showed a highly significant and positive association (Estimate = 315.928, p < 0.001), suggesting that aggressive behavior significantly increases accident risk.

Among the demographic factors, "Years of driving experience" was positively associated with accident frequency (Estimate = 9.93, p = 0.017), likely due to greater exposure over time. In contrast, "Age" was negatively associated (Estimate = -7.52, p = 0.011), indicating that younger drivers tend to be more accident-prone. Other variables, such as "Use of signal when changing lanes" and "Parking the car on traffic lanes," were not statistically significant, suggesting a limited individual contribution when controlling for other factors.

Table 5. Ordinal Logistic regression estimates for the impact of demographic and behavioral variables on the number of traffic accidents

Variable	Estimate	Wald	P-Value	Cl Lower	Cl Upper
Demographic Factors					
Sex	-1.36	0.859	0.354	-19.81	7.090
Age	-7.52	2.703	0.011	-12.44	0.51
Vehicle ownership	-6.47	5.084	0.024	-12.10	-0.847
Occupation	1.39	2.467	0.116	-0.347	3.143
Place of work or study	3.89	0.931	0.334	-41.12	120.906
Years of driving experience	9.93	5.725	0.017	3.86	15.95
Driving Behaviors					
Driving outside the speed limit	-73.10	4.049	0.044	-111.01	-34.97
Using a mobile phone while driving	-10.36	5.86	0.023	-19.22	0.82
Intentional obstruction	315.92	21.193	0.000	181.42	450.43
Chasing a vehicle	3.17	8.530	0.003	1.04	5.29
Sudden braking	-5.56	2.191	0.139	-210.49	29.36
Driving against traffic	-72.90	13.014	0.000	-113.34	-32.2
Use the signal when changing sides	-12.55	3.413	0.065	-25.87	0.76
Speaking loudly when provoked	-2.47	0.367	0.545	-247.61	130.66
Shift the path from the far right to the far left	3.44	3.262	0.071	-0.29	7.18
Passing from the right	-5.59	9.236	0.002	-9.20	-1.98
Slow driving on the Left Side	-1.62	2.023	0.155	-3.85	0.61
Respond when you are passed	1.17	1.737	0.188	-0.57	2.93
Parking the car on the traffic lanes	-9.65	1.642	0.200	-24.42	5.11

Model performance indicators are summarized in Table 6. The Model Chi-Square value (1877.682) indicates that the full model provides a statistically significant improvement over the null model ($p < 0.001$). The Nagelkerke R-square value was 0.944, suggesting that approximately 94.4% of the variance in accident frequency is explained by the model—a high level of explanatory power. The Deviance statistic (778.459) also supports model adequacy. Although the Test of Parallel Lines was not reported, the available metrics confirm that the model is statistically sound.

Table 6. Model fit statistics for the ordinal logistic regression

Statistic	Value
Model Chi-Square	1877.682
Deviance	778.459
Nagelkerke R-Square	0.944
Test of Parallel Lines	Not reported

These findings confirm the robustness of the ordinal logistic regression model in identifying key demographic and behavioral predictors of traffic accidents. The high explanatory power, alongside the significance of specific risky behaviors, underscores the importance of regulatory enforcement and targeted awareness campaigns aimed at reducing accident rates.

4. DISCUSSION

4.1 Overview of key findings

The statistical analysis revealed several significant demographic and behavioral factors that influence the frequency of traffic accidents. Both multiple linear regression and ordinal logistic regression equation were employed to ensure robust validation of the findings.

The ordinal logistic regression model identified age, vehicle ownership, and years of driving experience as significant demographic predictors. Among the behavioral factors, driving outside the speed limit, using a mobile phone while driving, intentional obstruction, chasing another vehicle, driving against traffic, and passing from the right showed statistically significant associations with accident frequency.

The linear regression model similarly confirmed the significance of several factors, including age, years of driving experience, place of work or study, sex, occupation, and behavioral factors such as driving outside the speed limit, using a mobile phone while driving, sudden braking, passing from the right, and responding when overtaken.

Notably, the ordinal logistic regression model demonstrated exceptionally high explanatory power (Nagelkerke R^2 = 0.944), while the linear regression model yielded a similarly strong adjusted R^2 of 0.984. These findings underscore the consistency and reliability of the identified risk factors and reinforce the value of combining multiple analytical methods to capture different dimensions of traffic accident causation.

4.2 Interpretation of significant predictors

The regression analyses identified several variables with statistically significant associations with the frequency of traffic accidents. Among the demographic predictors, age and years of driving experience consistently showed significant effects across both the linear and ordinal logistic regression equation. Younger drivers were found to be at greater risk of accidents, aligning with established traffic safety literature that links youth with inexperience, impulsivity, and a tendency toward risk-taking. Conversely, increased driving experience was associated with higher accident frequencies in the ordinal model—likely reflecting greater cumulative exposure over time.

Additionally, vehicle ownership was significant in the ordinal model ($p = 0.024$), with a negative estimate, suggesting that those who own their vehicles may experience fewer severe accident outcomes—potentially due to greater personal responsibility or vehicle familiarity.

In terms of behavioral predictors, driving outside the speed limits emerged as one of the most consistent and impactful contributors to accident occurrence, achieving statistical significance in both models. This supports the well-documented role of speeding in increasing crash risk.

Intentional obstruction was another major predictor, particularly in the ordinal logistic model, where it exhibited a high positive estimate (Estimate = 315.92, $p < 0.001$). Such aggressive behaviors—like deliberately blocking other vehicles—disrupt traffic flow and heighten collision risks.

Using a mobile phone while driving was statistically significant in both the linear ($p = 0.012$) and ordinal logistic regression models (Estimate = -10.36, $p = 0.023$), suggesting that mobile phone use elevates accident risk and increases the likelihood of falling into more severe accident categories. This likely reflects increased cognitive distraction and delayed reaction times under complex traffic conditions.

Other significant behavioral predictors included passing from the right (Estimate = -5.59, $p = 0.002$), chasing a vehicle (Estimate = 3.17, $p = 0.003$), and driving against traffic (Estimate = -72.90, $p < 0.001$), all of which represent aggressive or non-compliant behaviors that destabilize driving environments and increase collision probability.

In the linear regression model specifically, sudden braking ($p < 0.001$) and responding when overtaken ($p < 0.001$) were also found to be significant contributors. These findings emphasize the role of impulsive or defensive maneuvers in triggering accidents, particularly in urban driving contexts where vehicle spacing is limited.

Overall, the convergence of significant predictors across both regression models—particularly those related to aggression, distraction, and speed—reinforces their central role in shaping accident risk. These findings validate the robustness of the modeling approach and provide actionable insights for targeted interventions in driver behavior and enforcement policies.

4.3 Interpretation of non-significant predictors

While many predictors demonstrated strong statistical significance, several behavioral and demographic variables did not show a significant association with traffic accident frequency in either regression model. Specifically, using the signal when changing lanes, speaking loudly when provoked, and abrupt lane shifting from the far right to the far left failed to reach statistical significance. Although these behaviors are widely regarded as unsafe, their infrequent occurrence or limited variability in responses may have reduced their statistical impact. For instance, if most participants reported rarely or never engaging in these behaviors, the dataset would lack the distributional diversity necessary to detect meaningful correlations.

Additionally, slow driving on the left side did not show statistically significant effects in either model, suggesting that its impact may be context-dependent or mediated by other driving conditions not captured in the analysis.

This finding contrasts with previous research. For example, studies in Iran and India [13, 14] have identified distraction and verbal aggression as contributing factors to accidents, while studies in Japan and the UAE [5, 9] emphasized the role of situational behaviors—such as improper signaling—in crash risk. The lack of significance in this study may be due to contextual differences, such as stronger enforcement of specific behaviors, cultural norms around driving courtesy, or underreporting due to social desirability bias.

From a demographic standpoint, occupation did not demonstrate statistical significance in the ordinal logistic regression model. This suggests that job type alone may not directly predict accident involvement after controlling for other risk factors. Nevertheless, such variables may still play an indirect role through exposure frequency or type of driving (e.g., professional vs. personal), which were not modeled in detail.

In summary, the absence of statistical significance does not imply practical irrelevance. It highlights the complex and context-dependent nature of traffic accident causation, where some behaviors may only become statistically relevant under specific sample conditions or in interaction with other risk factors. This underscores the importance of interpreting quantitative findings within the broader behavioral and cultural context of the study population.

4.4 Policy and practical implications

The findings of this study have several important implications for traffic safety policies and intervention strategies, particularly in regions with similar driving environments to Al-Anbar Governorate. The identification of key behavioral predictors—such as speeding, intentional obstruction, using a mobile phone while driving, passing from the right, sudden braking (as identified in the linear regression model), and chasing other vehicles—underscores the urgent need for targeted awareness campaigns aimed at reducing these high-risk behaviors. Educational initiatives should highlight the dangers of speeding, sudden braking, and distracted driving, especially among younger drivers, who demonstrated elevated accident risk.

Enforcement also plays a crucial role. The statistical significance of aggressive and impulsive behaviors—such as intentional obstruction, overtaking from the wrong side, and driving against traffic—suggests that stricter application of traffic laws, including fines and license penalties, could help reduce accident frequency. Moreover, integrating behavioral assessments into driver licensing systems and renewal programs may help identify high-risk individuals and allow for targeted corrective training.

Urban and traffic planners should also integrate behavioral evidence into infrastructure design. For instance, the significance of passing from the right and sudden braking (in the linear model) highlights the need for improved lane discipline enforcement, clearer road markings, and adequate vehicle spacing policies to reduce rear-end collisions in accident-prone zones.

In summary, the study supports a multifaceted approach that combines education, enforcement, and engineering to address behavioral causes of accidents. The findings offer actionable guidance for policymakers and transportation authorities seeking evidence-based strategies to enhance road safety and reduce accident-related injuries and fatalities.

4.5 Comparison with previous studies

The findings of this study are largely consistent with existing international literature on driver behavior and accident risk. The significant effect of speeding aligns with multiple prior studies that identified excessive speed as a major contributor to traffic accidents, including research conducted in the United States [1], Saudi Arabia [10], and Iran [13]. Similarly, the role of aggressive behaviors such as intentional obstruction echoes findings from France [3] and China [6], where traits like hostility and competitive driving were linked to increased accident severity.

The observation that younger drivers are more accident-prone is supported by studies in Florida and Kuwait [1, 8], both of which highlighted the vulnerability of younger age groups due to inexperience, impulsivity, and peer influence. Conversely, the positive association between driving experience and accident frequency in the ordinal regression equation may reflect cumulative exposure over time—a pattern also observed in studies from North Cyprus and Ghana [11, 18].

Mobile phone use was statistically significant in both regression equation in this study, reflecting its growing impact on driver distraction. This finding aligns with results from India and Iran [13, 14], where phone use and other distraction-related behaviors were strongly associated with accident involvement, particularly in models sensitive to accident severity or driver subgroups.

Some behaviors, such as using turn signals, slow driving on the left, and abrupt lane shifting, were not statistically significant. While these results differ from expectations, similar patterns were documented in studies from the UAE and Japan [5, 9], where the effect of safety-related behaviors varied based on infrastructure design, driving culture, and enforcement levels. The lack of significance in this study may also be due to limited behavioral variation within the sample or underreporting due to social desirability bias.

Overall, the alignment with previous literature reinforces the external validity of the study, while divergences emphasize the importance of context-sensitive interpretations in traffic safety research, especially in culturally distinct and administratively diverse regions like Al-Anbar Governorate.

5. CONCLUSION

This study investigated the influence of driver behavior and demographic characteristics on traffic accident frequency in Al-Anbar Governorate, Iraq. Using a structured questionnaire distributed to 900 licensed drivers, the analysis employed both multiple linear regression and ordinal logistic regression to identify key predictors of accident involvement.

The findings revealed that speeding, using a mobile phone while driving, passing from the right, intentional obstruction, and chasing other vehicles were among the most statistically significant behavioral contributors to accident risk. Demographic factors such as age and years of driving experience also emerged as consistent predictors across both models.

In contrast, some behaviors widely regarded as risky—such as using turn signals, slow driving, or abrupt lane changes—did not demonstrate statistical significance. This underscores the importance of interpreting driver behavior in light of contextual, cultural, and enforcement-related factors unique to the study area.

These results emphasize the need for targeted awareness campaigns, stricter enforcement of traffic laws, and evidence-based interventions that prioritize the most influential risk factors. The study offers actionable insights for policymakers and traffic safety authorities seeking to reduce accident rates and improve road safety conditions in high-risk environments such as Al-Anbar Governorate.

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