International Journal of Safety and Security Engineering
Vol. 15, No. 5, May, 2025, pp. 913-923
Journal homepage: http://iieta.org/journals/ijsse

Impact of Road Geometry and Land Use on Motorcyclist Driving Stress

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https://doi.org/10.18280/ijsse.150506

Received: 13 February 2025
Revised: 20 March 2025
Accepted: 25 April 2025
Available online: 31 May 2025

Keywords:
driving stress, road geometry, land use, stress indicators, driving stress management

ABSTRACT

Driving stress among motorcyclists is a significant issue that increases the risk of traffic accidents and psychological strain, especially in urban areas of developing countries. This study aims to identify indicators of driving stress and analyze the impact of road geometry and land use on stress levels. The uniqueness of this study lies in integrating real-time physiological data from motorcyclists and analyzing road geometry and land use in Banda Aceh, Indonesia. Data were collected using wearable technology (Polar Vantage V2) to measure heart rate variability and a GoPro MAX 360 camera to capture road geometry and land use**.** The Multiple Indicators Multiple Causes (MIMIC) model was used to analyze the effects of these factors on motorcyclist stress. The results showed that heart rate levels were highest in office areas, at turns, and in locations with traffic controls such as lights and roundabouts. Land use variables, such as SDNN, RMSSD, and TINN, significantly influenced the time domain stress model. Road geometric variables significantly impacted the frequency domain stress model, including gradients, inclines, and bends with LF/HF (FFT) and LF/HF (AR). Findings can be used to educate the public and improve road safety assessments in emerging countries like Indonesia.

1. INTRODUCTION

Road rage is crucial in understanding the relationship between driving stress, risk inclination, and traffic sanctions [1]. Although generally overlooked by drivers, [1, 2], asserted that it predicts hazardous driving behavior. Tension can negatively affect driver performance, increasing the likelihood of traffic violations and the risk of road accidents [3-5]. Previous research highlighted that driving, a significant part of commuting, can be a complex and stress-inducing activity, often caused by interactions with other drivers [6, 7]. Moreover, prolonged driving can induce a continuous stress response [8]. Previous research has explored the influence of stress on driving performance, behavior, and road safety [9, 10].

In Indonesia, the accelerating pace of transportation and inadequate infrastructure contribute to congestion, longer driving times, and increased fatigue, which raise accident risks [11]. Continuous driving leads to fatigue and lethargy, increasing the likelihood of human error and accidents [12]. Aggressive driving, linked to road rage, significantly raises accident risks. Drivers who frequently violate traffic rules and understand speed limits tend to exhibit more aggressive behavior [13, 14]. Studies have identified hostile aggression associated with rage [15], and a meta-analysis demonstrates a strong correlation between driving rage and accidents [16]. Furthermore, drivers often exhibit anger as a coping mechanism in response to aggressive behavior from others. Research shows an association between anxiety and aggressive driving, with 80% of drivers reporting some anxiety, particularly among women over 35, where anxiety levels are higher than in men [17-19].

While problem-focused coping strategies were more commonly employed by drivers exhibiting instrumental rather than hostile aggression [20], numerous transportation challenges, such as traffic congestion, can significantly intensify driving stress. When the volume of vehicles surpasses the capacity of the road, journey times are adversely affected, thereby exacerbating stress levels and increasing the likelihood of accidents. As stipulated by Government Regulation No. 44 of 1993, article 240, paragraph 2, concerning Vehicles and Drivers, the maximum daily driving time is set at eight hours; exceeding this limit further exacerbates tension levels [21] further increases stress, while poor stress management impairs individuals' ability to interact with their environment [22].

In Indonesia, particularly Banda Aceh, high motorcycle dependency has led to greater accident exposure in urban areas [23]. As a growing capital city, Banda Aceh has experienced rapid development and congestion, contributing to 72% of traffic [23], driven by economic growth and supported by government investment in education [24]. With a population of 265,111 and a density of 43 people per, traffic pressure continues to rise. Motorcycles make up 80% of motorized traffic [25], with registrations increasing from 219,532 in 2020 to 250,154 in 2024, representing 13,95% of all vehicles [25-28]. This growth aligns with rising accidents involving motorcycles, pedestrians, and bicycles [29]. In 2020, there were 103,228 traffic incidents and 30,568 deaths in Indonesia, mirroring the global trend of road accidents being the leading cause of death among those aged 14 to 29 [30].

In Indonesia, three people die every hour due to road accidents, with 61% caused by human factors, 9% by vehicle issues, and 30% by infrastructure and environmental conditions [31]. Drivers under work-related stress tend to exhibit risky behavior, while those without stress are likelier to follow occupational safety practices [31]. Studies show men are more prone to unsafe driving than women, though experience reduces such tendencies [32]. The diverse traffic mix—cars, motorcycles, rickshaws, and more—adds complexity to road safety [33]. In Banda Aceh, traffic grows by 6% annually, driven by rising living standards and mobility demands [34]. Urban transport issues stem from uneven road networks, activity concentration, and a shift to private transport like motorcycles, prompting infrastructure expansion to meet growing regional mobility needs [35]. Additionally, extreme stress can trigger physiological responses such as increased heart and respiratory rates, dilated pupils, muscle contractions, and anxiety, further affecting driver behavior [36].

Previous research has shown that driving tension directly or indirectly contributes to traffic accidents among professional drivers [37], with a strong correlation between drivers' physiological responses and stress levels [38]. Meilinda [39] found that driving stress is associated with road geometry, particularly on curved roads and in office or industrial areas. Road design and urban spatial structure significantly influence how drivers manage vehicle movement and stress levels. In Banda Aceh City, changes in land use due to urban development indirectly affect traffic distribution patterns. Therefore, this study aims to examine the factors influencing motorcycle driving stress in Banda Aceh by analyzing road geometry and land use patterns. Data were collected using heart rate variability (HRV) and analyzed through a Multiple Indicators Multiple Causes (MIMIC) model.

2. MATERIALS

2.1 Driving stress

The relationship between driving behavior and stress was examined through the use of numerous questionnaire-based surveys. Stress, a state of mental or physical tension brought on by external and internal factors, is an unavoidable result of human existence. It is brought on by a variety of factors, including industrialization, urbanization, population growth, and various life issues. Travel is closely related to stress. Those who use motorized modes frequently experience stress due to the duration of their journeys. Factors such as congestion, parking issues, interactions with other motorists, and concerns regarding safety can all contribute to tension among automobile users [40]. Transportation decisions that result in challenges such as inadequate availability of green space [41] and traffic pollution [42] can also influence the stress levels of individuals. Additionally, public transportation users may experience anxiety due to factors such as lengthy wait periods, overcrowding, high fares, and unpredictability regarding routes and schedules. In addition to environmental factors, socioeconomic factors such as age, gender, education, occupation, income, and driving experience significantly impact the stress levels experienced by drivers [43].

To evaluate driving stress, various physiological responses, such as respiration rate and galvanic skin response, as well as instruments like electrocardiogram, electromyogram, electrooculogram, electroencephalograms, and pulse oximeters, have been utilized [38, 44]. Additionally, the conductivity of the skin and pulse rate parameters are strongly correlated with driving stress [38]. Among these variables, heart rate variable (HRV) is the most effective for assessing a driver's condition during travel [38]. HRV analysis, which is frequently used to detect actual driving tension, is based on heart rate variability, a measure of electrocardiographic activity [38, 45, 46]. Previous research has also utilized HRV to estimate mental exertion [38]. Research by Meilinda et al. [47] found that driving stress in motorcyclists, measured through heart rate (HR) and respiration rate (RR), showed abnormal values, indicating unsafe driving stress on urban arterial roads. Physiological responses to increased stress include heightened heart and respiratory rates, pupil dilation, muscle contractions, and anxiety [36, 38]. The relationship between prolonged driving and cardiovascular health is attributed to several mechanisms, such as prolonged sitting during driving, which may compromise cardio-metabolic health [48, 49].

Traffic congestion poses a significant problem worldwide, serving as the primary source of driving stress. This issue arises due to factors like high population density, continued infrastructure expansion, rising motor vehicle usage, and the proliferation of rideshare and delivery services [50]. The consequences of traffic congestion are far-reaching, affecting society, the economy, and the environment. By wasting time and energy, reducing productivity, causing pollution and stress, and hindering sustainable economic growth [51, 52], these effects are extensive and widespread. In response to traffic jams, many drivers feel compelled to increase their vehicle speed in order to arrive at their destination on time. However, driving at a high speed, particularly when anxious or distracted, significantly heightens the risk of accidents [38].

2.2 Heart rate (HR)

Heart rate, also known as the number of heart beats per minute, is typically expressed in beats per minute (BPM) [53, 54]. The wrist, beneath the brows, the side of the neck, and above the soles of the feet are among the body parts that can be used to measure heart rate; however, the wrist typically yields more accurate results [55]. During high-intensity activities, such as sports, the pulse rate tends to increase. This elevation in heart rate is necessary as the body requires oxygen-rich blood during exercise to perform optimally. As per the guidelines provided in Pediatrics for Medical Students [56], specific heart rate values are presented in Table 1. The heart rate variability (HRV), also known as RR interval, refers to the duration between two consecutive R waves, which are the waves with the greatest amplitude. This variable, HRV, is intimately connected to the human autonomic nervous system, which consists of two subsystems: the sympathetic and parasympathetic. The sympathetic nervous system triggers a faster and stronger heartbeat when the body is undergoing strenuous or distressing activities. Conversely, the parasympathetic nervous system promotes a slower and weaker heartbeat during relaxed and tranquil situations.

There are two primary methods of measuring HRV: time and frequency domain analyses. Time domain analysis is a simpler method that involves utilizing mathematical calculations to assess variation between multiple RR intervals [38]. This approach often employs standard heart rate monitoring devices with respiratory variability-supporting programs for recording. On the other hand, frequency domain analysis uses the Fourier transform and distinctions to differentiate between the frequency domains of the sympathetic and parasympathetic systems for computation. This method provides valuable insights into how the autonomic nervous system and the hypothalamus-pituitary-adrenal (HPA) axis control stress response. Clinically significant physiological responses, such as heart rate variability, blood pressure, and hormonal responses, including cortisol release, are important indicators [57]. In road driving scenarios, studies have found that the activation and inhibition of sympathetic and parasympathetic nerve activities, respectively, are linked to increased rear-end collision risk index levels. The results suggest that acute stress-induced driver fatigue increases the risk of rear-end collisions [58].

Table 1. Normal heart rate

Age	Heart Rate While Awake (bpm)	Heart Rate While Sleeping (bpm)
Neonatus (< 28 days)	100-205	90-160
Baby	100-190	90-160
Toddler (1-2 years)	98-140	80-120
Preschool (3-5 years)	80-120	65-100
Children (6-11 years)	75-118	58-90
Adult (> 18 years)	60-100	50-90

Source: Chris Novak dan Peter Gill, 2016 [56]

3. METHOD

3.1 Study area and data collection

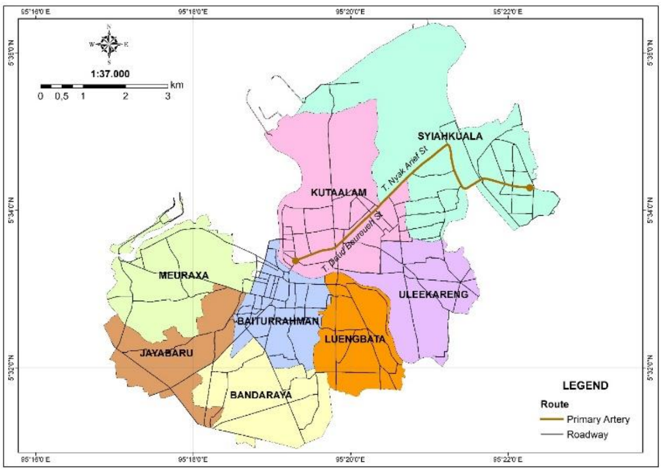

Figure 1. Area of the study (map created by the authors)

The study was conducted along the primary arterial road, specifically Jl. T. Nyak Arief and Jl. T. Muhammad Daud Bereueh. The road was divided into thirty 500-meter segments for each respondent. Figure 1 depicts the location of the primary arterial road in relation to this research. Over a period of approximately three months, from June 26 to August 10, 2022, a psychological indicators survey instrument was compiled for several respondents who were selected as research samples. Data collection sessions were scheduled during peak hours in the morning, afternoon, and evening, as well as on weekdays and weekends, based on the availability and approval of the respondents.

(a) (b)

Figure 2. (a) Vantage V2 polar watch [59]; (b) GoPro MAX 360 [60]

The instruments utilized in this research comprised a Vantage V2 polar watch and a GoPro Max 360 video camera, as depicted in Figure 2. The Vantage V2 polar watch was employed to acquire GPS data and featured a heart rate sensor. The participants donned polar watches equipped with close proximity sensors to guarantee accurate detection. These sensors then transmitted heartbeat signals to a receiving device operating the polar flow application. Conversely, the GoPro Max 360 video camera captured footage of various road conditions, such as highways, lanes, traffic lights, bridges, medians, and overall traffic conditions. Moreover, the sensor measured the heart rate of the subject 10 minutes prior to driving, serving as the primary condition or "rest condition," and while traveling along a predetermined route. The sensor then transmitted the heart rate signal to the Polar Vantage V2 watch, which was extracted using the Flow app. A total of 25 respondents were selected based on specific criteria, which included factors such as being in good health, holding a valid motorcycle driving permit, and a balanced representation of students and workers, as well as an equal number of males and females. Respondents were randomly selected to ensure diversity, and their willingness to participate in the research study was confirmed. Based on the outcome of the data evaluation, 22 datasets were collected, considering factors such as land use, road geometric and traffic control, from 25 respondents. Five hundred fifty (550) datasets were obtained for the primary arterial road.

3.2 Multivariate analysis with MIMIC model

The multiple-indicators multiple-causes (MIMIC) model is commonly employed in transportation research focused on travel behavior. This model is used to thoroughly examine individual behavior and the psychological perceptions of respondents [61]. In a study conducted in Jakarta, the SEM-MIMIC model was utilized to investigate the relationship between public perceptions of transportation system policies. Additionally, an in-depth analysis of public acceptance of transportation policies in Jakarta was conducted using the multiple-samples multiple indicators multiple-causes (MS-MIMIC) model [62, 63]. The objective of this analysis was to demonstrate the connection between travel behavior and public perception of transportation policy. The MIMIC model consists of structural equations and measurement models, as outlined in Eqs. (1) and (2).

$$\eta_i = B\,\eta_i + \Gamma z_i + \zeta_i \tag{1}$$

$$y_i = \Lambda\,\eta_i + \zeta_i \tag{2}$$

where, y_i is a vector of perception indicators (unobserved variables), z_i is a vector of observed variables η_i, $B,\ \Gamma, and\ \Lambda$ matrices of regression coefficients that must be estimated (unknown parameters), and ζ_i and $\zeta\ _i$ are vectors of measurement error. The Maximum Likelihood Estimator (MLE) method is implemented to determine unknown parameters, and its programming is executed using the SIMPLIS common language, as specified in reference [64]. Furthermore, the program is executed using LISREL 10.20 software. The MIMIC model incorporates unseen latent variables, which are assessed through various indicators and predicted by different causes. By conducting a thorough examination of each score of the research variables, the structural equation modeling (SEM) data analysis enables a comprehensive evaluation of the constructs. The questionnaires or statements used in the study are considered as either manifest or latent indicators of the variables being measured [65].

The MIMIC model establishes the connections between observable and unobservable variables by minimizing the distance between the sample covariance and the model-predicted covariance matrix. SEM analysis is particularly effective in addressing non-experimental research problems. The general SEM model comprises two components: the measurement component, which links the tested variables to the latent variables through a confirmatory factor model, and the structural component, which connects the latent variables through a set of equations simultaneously [65, 66]. In addition, it is common practice in the field of SEM to evaluate the validity and reliability of measurement instruments through confirmatory factor analysis [66, 67]. Specifically, this analysis is conducted in two stages: exploratory factor analysis and confirmatory factor analysis. Exploratory factor analysis is used to identify potential factors in the data, while confirmatory factor analysis is used to test and refine theoretical models over time [67, 68].

3.3 Data analysis method

The HRV parameters were preliminarily analyzed using Kubios HRV 3.5.0 software, followed by further analysis and calibration via the MIMIC method. This method employs the Maximum Likelihood Estimator in LISREL 9.2 software to estimate the parameters. The MIMIC model is designed to test the null hypothesis of the model and determine the vectors of indicator variables (y) linked by a latent variable (η) and a covariate (x). The model comprises two equations, one of which examines the relationship between (x) and (η) and the other confirms the relationship between (y) and (η). To evaluate the model's viability and the parameters' accuracy, Goodness of Fit (GoF) model testing will be performed. The GoF assessment will involve several metrics, including GFI (> 90%), AGFI (> 90%), CFI (> 90%), RMSEA (≤ 0.08), and T test for parameter significance <5% [61, 62, 69, 70].

4. RESULTS

4.1 Distribution of respondent's demographics

The data collected from the participants primarily consisted of demographic information, including their age, gender, education level, occupation, travel purpose or intention, monthly family income, motorcycle ownership, and possession of a two-wheeled driving license. The participants were predominantly male (56%), with the majority falling within the age range of 20 to 29 years. Females made up the remaining 44%, with their ages ranging from 17 to 19 years. In terms of education, most participants (68%) were undergraduate graduates, while primary school graduates/equivalents accounted for 28%. In terms of occupation, the respondents were divided into private employees (16%), self-employed individuals (4%), students (40%), and others (40%). The primary travel purposes of the participants varied, including business or work, education, shopping, and vacation, and accounted for 8%, 24%, 36%, and 32%, respectively. The frequency of daily trips ranged from 2 to more than 5 times a day, with 44% of participants making 2 trips, 40% making 3 trips, 8% making 4 trips, and 8% making more than 5 trips. Monthly family income was distributed across different brackets, with 48% earning between 3 to 4.9 million IDR (*1 USD approximately 15,880 IDR*), 20% each earning between 5 to 6.9 million and 7 to 9.9 million, 8% earning between 1 to 2.9 million, and 4% earning more than 10 million. Motorcycle ownership varied, with 28% owning 1 unit, 12% owning 2 units, 44% owning 3 units, 4% owning 4 units, and 16% owning no units. Furthermore, each participant possessed a driving license.

The assessment of autonomic nervous system activity was carried out by analyzing HRV parameters. The parameters examined included the RR, standard deviation of normal to regular RR intervals (SDNN), mean root square of successive differences RR intervals (RMSSD), and Triangular interpolation (TINN). Additionally, the balance between sympathetic and parasympathetic nervous system activities was evaluated using the Low Frequency (LF)/High Frequency (HF) ratio derived from fast Fourier transform (FFT) analysis. The values were calculated using the widely recognized Kubios HRV 3.5.0 software (www.kubios.com), which is a scientific lite version of the software. It is free HRV analysis software that offers limited functionality and is intended for non-commercial use only. This software supports RR data from HR monitors and provides basic HRV analysis features.

4.2 Distribution of respondent's HRVs

The assessment of autonomic nervous system activity was carried out by analyzing HRV parameters. The parameters examined included the RR, standard deviation of normal to regular RR intervals (SDNN), mean root square of successive differences RR intervals (RMSSD), and Triangular interpolation (TINN). Additionally, the balance between sympathetic and parasympathetic nervous system activities was evaluated using the Low Frequency (LF)/High Frequency (HF) ratio derived from fast Fourier transform (FFT) analysis. The values were calculated using the widely recognized Kubios HRV 3.5.0 software (www.kubios.com), which is a

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Table 2. The average value of the parameter HRV

Indicators	Mean of HR	Mean of RR	SDNN (ms)	RMSSD (ms)	TINN (ms)	LF/HF (FFT)	LF/HF (AR)
Land Use							
Education area	93.056	650.382	19.710	10.715	83.800	9.016	10.173
Office	**94.029**	644.113	12.000	6.407	50.540	9.439	20.947
Housing area	93.174	650.340	7.747	4.288	25.176	6.063	21.380
Security and safety	92.533	657.485	16.060	8.764	58.260	14.240	17.569
Trading	93.789	647.818	11.685	5.737	39.738	8.883	55.247
Worship	92.813	655.578	7.530	5.406	27.813	4.253	11.898
Green open space	93.647	648.517	8.325	6.803	31.000	4.888	13.055
Health center/hospital	93.221	651.748	12.336	4.879	35.320	15.003	22.061
Road Geometric							
Straight	92.836	653.517	15.538	8.782	63.991	9.332	11.610
Turns/bends	**94.244**	644.782	11.601	5.655	37.814	9.335	63.376
Bends and climbs	93.302	650.651	7.869	5.214	22.560	6.829	12.832
Derivative	93.821	647.475	7.672	4.551	26.445	8.931	21.577
Incline	93.568	648.875	7.303	4.465	25.200	6.179	27.404
Turn and derivative	93.863	646.422	6.093	4.478	21.800	2.578	22.478
Traffic Control							
N/A	93.198	651.255	11.467	6.823	44.361	6.412	26.929
Traffic Light	94.137	644.169	12.290	5.951	44.152	14.456	28.430
Roundabout	92.172	663.535	13.846	7.575	40.880	5.901	13.649
Traffic light and Roundabout	**94.976**	640.256	9.992	5.130	34.590	11.692	29.322

Table 2 presents a comparison of heart rate across various land use conditions and road geometric features. The data indicates that office areas recorded the highest heart rate at 94.03 beats per minute, while areas designated for security and safety areas had the lowest, at 90.99 beats per minute. In terms of road geometric conditions, U-turns, curvature, and straight roads recorded the maximum and minimum heart rates of 94.24 bpm and 92.84 bpm, respectively. Additionally, traffic control elements such as traffic lights and roundabouts recorded a maximum heart rate of 94.98 beats per minute.

The findings demonstrate how an individual's degree of physical activity and heart health can be impacted by the surrounding environment, including land use and road features. Stress hormones like cortisol and adrenaline can be released by drivers' autonomic nervous system in response to stress. This may result in an elevated heart rate as the body reacts to an anxious or tense circumstance [71]. The location with the highest heart rate, 94.03 bpm on average, was the office area. High levels of physical activity or stress from the workplace setting, such as rush-hour traffic, parking space constraints, and more frequent encounters with pedestrians and other vehicles, may be the cause of this. The driver typically has a high heart rate as a result. At an average heart rate of 90.99 bpm, the security and safety zones reported the lowest heart rates. A lower heart rate may be influenced by the less stressful atmosphere and more controlled traffic in certain places.

Turns also had the highest heart rate, average 94.24 bpm, on record. This is brought on by abrupt direction shifts and turning that requires more physical effort. However, with an average heart rate of 92.84 bpm, the lowest heart rate was observed on a straight road. This is because drivers can keep a more constant speed on straight roads because there is less variance in their physical activity when driving on them. With an average heart rate of 94.98 bpm, this study also revealed that traffic management features including roundabouts and traffic lights had the greatest heart rates. This is brought on by circumstances that call for an immediate reaction and elevated tension when dealing with these factors. Several drivers at the intersection are the cause of the abrupt lane changes [36]. When changing lanes that need their attention, drivers experience driving stress, as shown by earlier studies [40].

However, this study discovered that limiting traffic regulation to roundabouts can reduce the average heart rate of drivers. his is due to the fact that roundabouts are made to make traffic flow easier without impediments like red or yellow lights, which lessens driver anxiety. Ultimately, there's no need to halt or decelerate the vehicle abruptly. Additionally, drivers typically do not have to wait for a traffic light to turn green, which can reduce frustration and anxiety because drivers feel more efficient in their travels. When compared to intersections with traffic signals, roundabouts often have lower accident rates. This is a result of the constant flow of traffic without abrupt stops, which lessens the chance of lateral or rear-end crashes.

Prior studies have also demonstrated that roundabouts, as opposed to traffic lights, are more successful in lowering stress levels; this may be because roundabouts have shorter wait times. Longer waiting times can increase stress levels [38]. Ni, Jie, et al. [40] observed that stress levels were elevated by delays and speed decreases related to stop-controlled junctions. Most significantly, research has shown that, as compared to traditional intersections managed by stop lights and signs, roundabouts reduce crashes that result in serious injury or death by 78-82% [72].

4.3 Result of MIMIC model

The MIMIC model was employed to investigate the relationship between stress variables in both the time and frequency domains, and HRV parameters (X variable), as well as their connection with land use procedures and road geometric (Y variable) indicators. The analyzed HRV parameters encompassed RR, the standard deviation of normal to regular RR intervals (SDNN), the mean root square of successive differences RR intervals (RMSSD), Triangular interpolation (TINN), and the balance between sympathetic and parasympathetic nervous system activity represented by the Low Frequency (LF)/High Frequency (HF) ratio obtained through fast Fourier transform (FFT). These parameters were selected due to their sensitivity in capturing physiological changes associated with autonomic nervous system responses to external driving stimuli.

In this study, sympathetic, and parasympathetic nervous system arousal were considered. The time domain method comprised five parameters, RR, and mean HR, which were excluded from latent variables due to lack of fit with the model. Nonparametric and parametric methods were used, such as the LF/HF (FFT) and LF/HF (AR) indicators, respectively. Of the various factors, significant effects were observed only for land use related to offices and education, as well as road geometric factors such as U-turns and curvature with ascents and descents. Meanwhile, other variables did not meet model criteria and were categorized as insignificant after multiple trials. Figure 3 displays the hypothetical model with common values, illustrating how land use and road geometric impact vehicular stress across time and frequency domains. Causal relationships between variables and significance levels were depicted with one-way arrows, with $^*p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$, respectively.

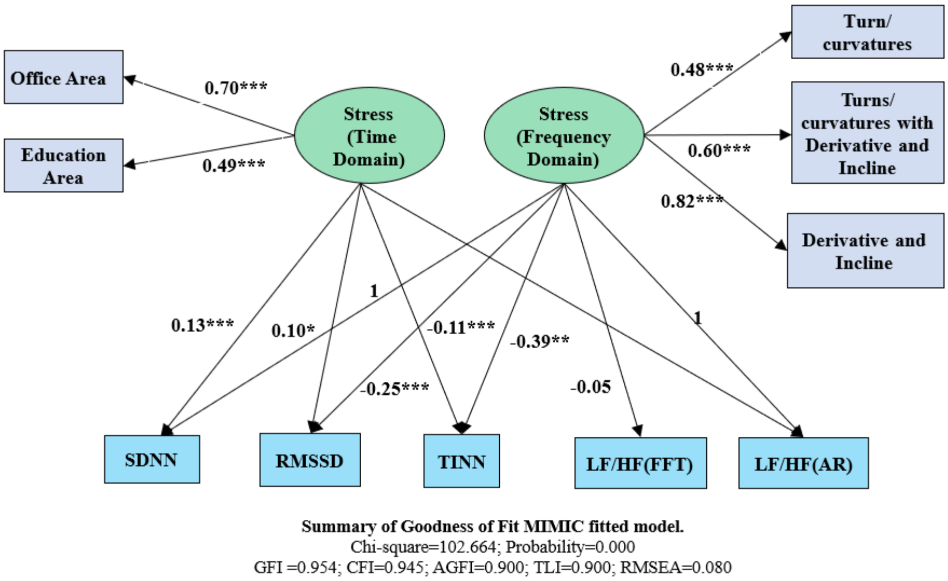

Figure 3. MIMIC stress time domain and frequency domain models

Table 3. Calibrated parameters for time domain and frequency domain stress model

Path Across Parameters			Loading Coefficients	Sig. T-Test (p-Value)
Stress Time Domain	←	Office	0.702	***
Stress Time Domain	←	Education Area	0.486	0.002
Stress Frequency Domain	←	Turns/Bends/Curvatures	0.479	***
Stress Frequency Domain	←	Turns/ Bends/Curvatures with Derivative and Incline	0.597	***
Stress Frequency Domain	←	Derivative and Incline	0.821	***
SDNN	←	Stress Time Domain	0.125	***
RMSSD	←	Stress Time Domain	0.102	0.009
TINN	←	Stress Time Domain	0.241	
LF/HF (AR)	←	Stress Frequency Domain	0.204	
LF/HF (FFT)	←	Stress Frequency Domain	-0.052	0.353
LF/HF (AR)	←	Stress Time Domain	-0.108	0.038
SDNN	←	Stress Frequency Domain	-0.300	***
RMSSD	←	Stress Frequency Domain	-0.251	
TINN	←	Stress Frequency Domain	-0.386	***

Note:

← = Causal relationships between variables parameters in the model

*** = Significant at 1% level

** = Significant at 5% level

* = Significant at 10% level

Table 3 displays the significance values for each parameter. It is clear that while there is no significant correlation between stress domain frequency and LF/HF (FFT), other variables have significant correlations. The Chi-Square correlation is used to assess the overall fit of the model, with a recorded value of 102.664. The fit of the MIMIC stress model is deemed acceptable in both time and frequency domains, with a Goodness-of-Fit statistic (GOF), Comparative Fit Index (CFI), Adjusted Goodness-of-Fit Index (AGFI), Tucker Lewis Index (TLI), and Root Mean Square Error Approximation (RMSEA) of 0.954, 0.945, 0.900, 0.900, and 0.080, respectively.

5. DISCUSSIONS

Based on the reference range of 60 to 100 beats per minute in Table 2, which represents the normal adult heart rate, the derived heart rate (HR) value suggests that the driver's overall condition is approaching the stress threshold. The term bradycardia refers to an irregular heartbeat where the heart's rhythm drops to or below 60 beats per minute [73]. Similarly, tachycardia is a condition characterized by a heart rate exceeding 100 beats per minute [53]. It is worth noting that urban areas with geometric curves or bends tend to elicit the highest heart rates. Interestingly, the research findings indicate that the threshold at which an individual's heart rate falls below the normal limit is only 6%.

This research highlights the relationship between driving stress due to the influence of differences in land use and road geometry in urban arterial road areas using the heart rate variability (HRV) method with two approaches, namely stress time domain and stress frequency domain. The evaluation and interpretation of heart rate fluctuations is the primary distinction between the HRV analysis's stress time and frequency domains. The stress time domain focuses more on the general fluctuation of heart rate over a certain period, while the stress frequency domain focuses more on the distribution of heart rate activity in various frequency ranges related to autonomic nervous activity. These two approaches can provide insights into drivers' physiological reactions of drivers to different driving conditions and traffic patterns.

The empirical results showed the tendency distribution of driver characteristic data, with the stress time domain significantly affected by the type of office land use. Stress based on the heart rate cadence of the driver had a greater impact on inanimate objects, such as infrastructure and land use, than on the driver. Tension from the nervous system tended to significantly affect objects in direct contact with the driver, such as geometric conditions of road bends, ascents, and descents. Increased stress was attributed to high traffic congestion, particularly evident during rush hour when the observations were conducted. Therefore, it was assumed that office areas also experienced heightened traffic congestion. Mixed traffic congestion in these areas during peak hours further increased stress levels in drivers.

This study demonstrates how land use characteristics, like traffic density, the kind of driving behaviour, and the placement of buildings or other infrastructure, can influence the level of activity and distractions experienced by drivers. For instance, a high traffic density near offices might lead to higher levels of stress and tension, which can be measured by a faster heart rate. Stress from driving is highly impacted by the office land use variable (standardized coefficient=0.70, $p < 0.01$). Because of the rush hour, loud surroundings, and concentration of cars, hectic office spaces might make drivers more stressed. The motorist may experience an increase in heart rate in response to stress due to all of these factors affecting their cardiac rhythm. High traffic and congested locations, such industrial districts (non-standardized coefficient=0.39, p=0.05, standardized coefficient=0.12), might make drivers feel more stressed out. Heavy traffic, truck, and mixed-road uses also have a positive and significant impact on driving stress [38]. Heavy traffic is frequently seen in industrial and office locations, especially during rush hour when workers are commuting to and from work. Drivers may experience tension and anxiety due to this dense traffic.

Additionally, driving stress is highly impacted by the educational land use variable (standardized coefficient=0.49, p=0.002). The driver's route included an elementary school and a state institution. The findings indicate that drivers may experience stress when operating a vehicle in an educational setting because of the requirement to protect children's safety and security, particularly in the vicinity of primary schools. Stressful situations for drivers include having to watch out for pedestrians, potentially careless kids, and unique traffic patterns around schools. Areas around schools also often have limited parking, which can make drivers spend more time relocating their vehicles. Furthermore, drivers may feel more stressed because of the busy and boisterous environment surrounding schools, particularly at the start and end of the day. These factors were obtained from direct observations in the field after being carried out several times at the research location.

However, some elements can give the driver a direct physical stimulus, like turn in the road (standardized coefficient=0.48, p=0.01), turns with derivative and incline (standardized coefficient=0.60, p=0.01), and incline conditions and derivatives (standardized coefficient=0.82, p=0.01). Road conditions, steep inclines, and sharp turns can all make it more difficult for drivers to maintain focus, control, and motor reaction, which in turn can make them feel more stressed. Nervous system-related stress reactions, such heightened attention, tense muscles, or elevated adrenaline, are more closely linked to the physical state and perception of the driving environment by the driver. Road geometry conditions that are hazardous or physically taxing can trigger this physiological stress response.

Driving around a bend can be challenging for drivers because of derivation and inclination bends. This may be the result of the slope decreasing line of sight and obstructing the view. Additionally, drivers need to be able to anticipate how the car would react to variations in road height. Similar results were shown from research [36], which stated that segments sharp turns can cause driving stress because the driver concentrates on the sharp turns and vehicles from the opposite direction. On the other hand, the fact that sharp turns are places where dangerous maneuvers cause driving stress is in line with previous research [74].

Land use conditions therefore have a substantial impact on stress based on heart rhythm since they affect the driver's degree of activity and distractions. On the other hand, as they affect the driver's physical and physiological sensations, road geometry can have a substantial impact on stress that is based on the nervous system. The combination of these two elements creates a convoluted driving environment and influence drivers' stress responses around areas with heavy traffic. Finally, it should be noted that locations with mixed and confused traffic, lane changes, road crossings, sharp turns, and traffic jams all cause the most driving stress.

This research also emphasizes the importance of the interaction between land use conditions and road geometry in influencing driver stress levels. The practical implications of these findings are highly relevant for urban planning, traffic safety, and transportation policy. Identifying areas with a high potential for driving stress such as office, industrial, and educational zones can support the development of more targeted interventions to reduce the psychophysiological burden on motorcycle riders. Strategic measures may include installing speed-calming devices (e.g., roundabouts or speed bumps), improved signage, and better road design in high-risk areas such as sharp curves, steep inclines, and congested urban corridors. A deeper understanding of how environmental factors contribute to driver stress can facilitate the creation of safer, more adaptive, and human-centered traffic systems.

Moreover, the study recommends integrating physiological data from drivers such as heart rate variability monitored through wearable devices into smart urban traffic management systems. This approach enables dynamic identification of high-risk road segments and can inform responsive safety measures. In the long term, urban zoning policies may consider the health implications of stress exposure, especially for motorcyclists, and support spatial separation between high-activity zones (e.g., offices and industrial areas). The study also contributes to developing Intelligent Transportation Systems (ITS), particularly for two-wheeled vehicles, which have often been overlooked in such innovations. Integrating biometric data into vehicle design or navigation systems could enhance driving safety by providing real-time alerts in high-stress areas or suggesting alternative routes. Therefore, the outcomes of this research not only enrich the academic discourse but also offer actionable insights for policymakers and urban planners to establish safer and more responsive urban transportation networks.

6. CONCLUSIONS

This research used the MIMIC model to examine the relationship between stress in both time and frequency domains, as well as HRV parameters (SDNN, RMSSD, TINN, LF/HF (FFT), LF/HF(AR)), with factors such as land use and road geometry. The study shows that factors like land use and road geometry have a significant impact on motorcyclists' stress levels. Office areas and sharp turns recorded the highest heart rates, indicating higher stress levels. Additionally, land use influences time domain stress, while road geometry has a greater impact on frequency domain stress. The study found that about 6% of heart rates exceeded the normal limit of 100 bpm, indicating potential stress. These findings emphasize the importance of further research to validate the results and assess the influence of external factors, such as weather and traffic conditions, on motorcyclist stress.

The implications of these findings for road safety are significant. Higher stress in specific areas, such as office zones or sharp turns, indicates that these areas may pose a higher risk to riders. Therefore, road infrastructure planning and improvements, such as redesigning roads and optimizing land use, could help reduce stress levels and enhance rider safety. The study also highlights the need for policies that can reduce stress-inducing factors while ensuring that road infrastructure supports riders in minimizing tension during their travels.

The research further suggests that additional studies are required to validate the findings and deepen our understanding of driving stress after initial investigations are completed. Consistent assessment is also crucial to ensure the effectiveness and sustainability of initiatives aimed at reducing driving stress. Some limitations of this study include significant variations in subjective reactions to stress while driving, as well as the influence of external factors like weather, traffic, and road conditions, which may affect the outcomes. Therefore, future research is expected to take these external factors into account and use larger samples to generate more comprehensive stress mapping, as well as explore the relationship between drivers' stress levels and their socioeconomic attributes.

DECLARATION OF COMPETING INTEREST

The authors affirm that they do not possess any identifiable personal relationships or competing financial interests that might have appeared to exert an influence on the research presented in this article.

ACKNOWLEDGMENT

The authors are grateful to Universitas Syiah Kuala for financially supporting the Program Riset Unggulan Universitas Syiah Kuala Percepatan Doktor (PRUU-PD), Lembaga Penelitian dan Pengabdian Kepada Masyarakat (LPPM) through contract 487/UN11/SPK/PNBP/2022.

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