Transportation Research Interdisciplinary Perspectives 34 (2025) 101743

Contents lists available at ScienceDirect

Transportation Research Interdisciplinary Perspectives

journal homepage: www.sciencedirect.com/journal/transportation-research-interdisciplinary-perspectives

Exploring risky riding behaviors and road safety outcomes among motorcycle taxi riders in Dar es Salaam, Tanzania

Katondo Salvatory Nambiza [a,1,*], An Neven [a,2], Wilfred Gordian Kazaura [b,3], Muhammad Wisal Khattak [a,4], Kris Brijs [a,5]

[a] Transportation Research Institute (IMOB), Hasselt University, Martelarenlaan 42, 3500 Hasselt, Belgium

[b] School of Spatial Planning and Social Science, Ardhi University, P.O. Box 35176, University Road, Observation Hill, Dar es Salaam, Tanzania

ARTICLE INFO

Keywords:
MRBQ
Risky riding
Behavioral safety
Motorcycle taxis
Road safety
Dar es Salaam

ABSTRACT

Motorcycle taxi riders (MTRs) are central to urban mobility in low and middle-income countries (LMICs) but experience a disproportionate burden of traffic injuries. In Dar es Salaam (DSM), Tanzania, motorcycle-related crashes remain persistently high. Yet, empirical studies on behavioral risk factors among MTRs are limited. This study aimed to adapt and validate the Motorcycle Rider Behavior Questionnaire (MRBQ) and examine associations between self-reported risky riding behaviors and road safety outcomes among MTRs in DSM.

A cross-sectional survey was conducted with 463 MTRs using an interviewer-administered, Swahili-translated version of the MRBQ, expanded with nine context-specific items. Principal component analysis with varimax rotation identified five behavioral domains: stunt behaviors, safety equipment use, traffic errors, traffic violations, and contextual risky behaviors. A multivariate probit model showed that traffic errors and contextual risky behaviors were strongly associated with crashes and near-crash involvement. Stunt behaviors were also positively associated with crash risk, while consistent use of safety equipment was linked to a reduced likelihood of being fined. Descriptive findings revealed near-universal helmet use but inconsistent adoption of other protective gear. Riders frequently engaged in locally common behaviors such as overloading passengers and riding on unauthorized roads. These practices appear to reflect adaptive responses to poor infrastructure, limited enforcement, and economic pressure. The findings support targeted, context-sensitive interventions aligned with Safe System principles. Future research should replicate this approach in other LMIC urban settings and explore behavior change strategies to reduce crash risk.

1. Introduction

Motorcycle-related crashes are a significant public health concern in Africa and other low- and middle-income countries (LMICs), where motorcycles often serve as the primary mode of transportation (Cholo et al., 2023). According to the World Health Organization (WHO), road traffic injuries resulted in approximately 1.19 million deaths in 2021, with motorcyclists accounting for 30 % of fatalities, despite representing only about 30 % of the global mobility (Gupta et al., 2023; WHO, 2023). LMICs contributed over 90 % of these deaths, despite possessing around 60 % of the global vehicle fleet (WHO, 2023). This burden is particularly concentrated in urban areas, where rapid motorization has outpaced the development of traffic safety enforcement and infrastructure.

In Tanzania, motorcycle taxis (locally known as *bodaboda*) play a vital role in urban and *peri*-urban mobility, especially in Dar es Salaam (DSM), the nation's largest city. These services are valued for their affordability, maneuverability in congestion, and ability to access underserved areas (Ehebrecht et al., 2018). However, this rapid growth has been accompanied by persistently high rates of crashes and fatalities. Between 2019 and 2024, motorcycles accounted for 21–23 % of all road traffic fatalities in Tanzania, despite comprising only 4.9 % of urban trips (Ibrahim et al., 2023; Tanzania Police Force, 2019, 2020, 2023,

* Corresponding author.
[1] https://orcid.org/0009-0004-6980-1575.
[2] https://orcid.org/0000-0003-0165-1799.
[3] https://orcid.org/0009-0000-9511-1536.
[4] https://orcid.org/0000-0002-0187-2519.
[5] https://orcid.org/0000-0002-1542-5496.

https://doi.org/10.1016/j.trip.2025.101743
Received 10 June 2025; Received in revised form 11 November 2025; Accepted 12 November 2025
Available online 16 November 2025

2024). In 2023 alone, motorcycles were involved in 435 crashes, resulting in 376 deaths, a 13.3 % increase from the previous year (Tanzania Police Force, 2023). DSM consistently records the highest crash burden, with human-related risk factors such as unsafe riding behaviors cited as key contributors (Tanzania Police Force, 2023, 2024).

Political dynamics also shape the bodaboda sector in DSM. Riders are frequently mobilized for electoral campaigns, political rallies, and protests, often receiving informal protection or material incentives in return (Malima, 2024; William, 2022). This politicization influences how riders perceive law enforcement and risk, distinguishing DSM from other LMIC contexts. Consequently, behavioral frameworks developed elsewhere may not fully capture the socio-political and occupational realities of motorcycle taxi riders (MTRs) in DSM.

Globally, the Motorcycle Rider Behavior Questionnaire (MRBQ) has been widely used to assess motorcyclist behavior, particularly in high-income and middle-income countries. The tool has been adapted and validated in diverse LMIC contexts, including Pakistan, Vietnam, India, Colombia, Malaysia, and Thailand, with studies demonstrating varied factor structures and behavioral predictors of crash involvement (Ahmad et al., 2022; Bui et al., 2020; Kumar et al., 2024; Laphrom et al., 2024; Ospina-Mateus et al., 2021; Pervez et al., 2024, Pervez et al. (2025a)). However, these studies primarily focus on general riders or delivery riders, with limited attention to commercial MTRs in sub-Saharan African cities.

To date, only four MRBQ-based studies have been conducted in sub-Saharan Africa, three in Nigeria and one in Tanzania. The Tanzanian study by Perego et al. (2024) analyzed MRBQ data from general motorcyclists in Arusha. However, it did not distinguish between private and commercial riders. Given DSM's unique transport dynamics, characterized by political embeddedness, denser traffic conditions, and a larger bodaboda fleet, a critical gap remains in evidence regarding how MRBQ behavioral constructs operate among commercial MTRs in such urban African settings.

This study addresses that gap by adapting and validating the MRBQ for use among MTRs in DSM, thereby generating context-specific insights into risky riding behaviors and contributing to the broader evidence base on road safety in LMICs.

The objective of this study was to examine risky riding behaviors and their associations with road safety outcomes among MTRs in DSM. Specifically, the study:

1) Assessed the prevalence and patterns of self-reported behaviors using an adapted version of the MRBQ;
2) Explored the factor structure of the adapted MRBQ to validate its relevance in the Tanzanian context;
3) Examined associations between MRBQ-derived behavior factors and three safety outcomes: crash involvement, near-crashes, and traffic fines.

2. Literature review

The MRBQ, developed by Elliott et al. (2007), has become a key instrument for assessing risky motorcycling behaviors. Initially designed with five behavioral domains — traffic errors, control errors, speed violations, stunts, and safety equipment use — the MRBQ has been validated in diverse settings using factor analyses and regression models. Its adaptability has led to widespread use in both high-income countries (e.g., UK, Belgium, Australia) and LMICs such as Pakistan, Vietnam, and India (Bui et al., 2020; Elliott et al., 2007; Kumar et al., 2024; Pervez et al., 2024, Pervez et al. (2025a); Schreurs et al., 2023; Stephens et al., 2017). These studies have revealed that behavioral predictors of crash outcomes can vary significantly depending on the context, rider demographics, and road conditions. A summary of these studies is presented in Table 1 below.

In high-income contexts, traffic errors and stunt behaviors often emerge as key predictors of crashes. For example, in the UK, Elliott et al.

Table 1
Summary of MRBQ-based studies predicting crashes, near-crashes, and traffic offenses.

Authors (Year), Country	Sample (size, population)	Methodology (MRBQ version)	Key Findings
Elliott et al. (2007). UK	N = 8,666 general motorcyclists	Original 43-item MRBQ; PCA (5-factor structure; traffic errors, control errors, speed violations, stunts, and safety equipment); GLM for crash prediction	Traffic errors and speed violations were found to predict crash risk in this first formal MRBQ validation study.
Sunday & Akintola (2010). Nigeria	N = 500 general motorcyclists	Adapted 40-item MRBQ; PCA (4 factors: speed/ impatience, error, stunt, and control/ safety); GLM	Speed/impatience and alcohol use predicted crash involvement.
Sunday (2010). Nigeria	500 commercial motorcycle riders	Adapted MRBQ; PCA; 4-factor structure: Control/ Safety, Stunt, Error, Speed/Impatience; GLM for crash prediction	Speed/impatience, experience, alcohol use, and motorcycle usage significantly predicted crash liability.
Motevalian et al. (2011a). Iran	N = 518 commercial delivery riders	Adapted MRBQ (48 items); 6 factors: Speed Violations, Traffic Errors, Safety Violations, Traffic Violations, Stunts, Control Errors; PCA	Violation factors were more strongly correlated with aggression than 'error' factors. Safety violations were the most frequently reported behaviors.
Özkan et al. (2012), Turkey	N = 451 general motorcycle riders	Turkish MRBQ (43 items); 5 factors: Speed Violations, Traffic Errors, Safety Equipment Use, Stunts, Control Errors; PCA	Stunts predicted active crashes and offenses; speeding violations predicted offenses. Rider behavior was associated with constructs from TPB, HBM, and Traffic Locus of Control.
Sakashita et al. (2014), Australia	N = 1,305 novice motorcycle riders	Original 43-item MRBQ; EFA, CFA;4-factor structure (Errors, Speed Violations, Stunts, Protective Gear), logistic regressions	Stunts predicted police-recorded crashes; Protective Gear predicted police-recorded offences.
Stephens et al. (2017). Australia	N = 470 general motorcyclists	Adapted MRBQ (29 items); EFA (5-factor solution: Traffic Errors, Speed Violations, Protective Gear, Control Errors, Stunts); Binary logistic regression.	Stunts predicted crash involvement; speed violations and control errors predicted near-crashes and speed-related offenses.
Topolšek & Dragan (2018). Slovenia	205 recreational riders	Original 43-item MRBQ + 2 custom perception instruments; SEM; 5-factor model: Errors, Speed Violations, Stunts, Safety Equipment, and Perceptual Factors	Perceived risks (e.g., alcohol, protective gear) predicted MRBQ behaviors. Older riders avoided stunts; training reduced errors; crash history was not associated with safer behavior. Experienced riders and those with high mileage were more

(continued on next page)

Table 1 (*continued*)

Authors (Year), Country	Sample (size, population)	Methodology (MRBQ version)	Key Findings
			likely to exhibit risk-taking behavior.
Bui et al. (2020). Vietnam	N = 2,254 general motorcyclists	Adapted 36-item MRBQ; EFA (4 factors: Control Errors, Traffic Errors, Safety Equipment, Speed & Alcohol Violations); Negative binomial regression	Traffic and control errors, as well as speed/alcohol violations, were all predictive of outcomes; however, the use of protective gear was unexpectedly linked to a higher crash risk.
Oluwadiya et al. (2020). Nigeria	500 MTRs	Modified 40-item MRBQ; PCA with Varimax; (4 factors: Control/Safety, Stunts, Error, Speed/Impatience). GLM for crash predictors	Only speed and impatience were significantly predictive of crash involvement. Other predictors: less experience, alcohol use, and non-commercial use.
Uttra et al. (2020b). Thailand	1,516 general motorcyclists	Adapted MRBQ; EFA and CFA; 26 items retained across four factors: Traffic Errors, Control Errors, Stunts, Safety Equipment.	Safety equipment had the most substantial factor loadings, and speed violations were integrated into the category of traffic errors. Helmet use was excluded due to low variability in the data.
Ospina-Mateus et al. (2021). Colombia	N = 438 MTRs	Adapted MRBQ; EFA (5 factors: stunts, speed violations, traffic errors, control errors, and safety gear use); Logistic regressions for multiple outcomes	Stunts linked to traffic tickets; control/traffic errors predicted crashes and near-crashes.
Chouhan et al. (2021). India	N = 392 general motorcyclists	Modified 36-item MRBQ; EFA (PAF; 4 factors: Traffic Errors, Control Errors, Speed Violations, and Stunts); Negative binomial regression for predicting crashes, near-crashes, and violations	Traffic errors were the strongest predictor of crash and near-crash; male riders and those with higher riding exposure were at significantly greater risk. Stunts also predicted crash outcomes. Speed violations and control errors were negatively associated with crash risk. No MRBQ factor predicted traffic violations.
Setoodehzadeh et al. (2021). Iran	N = 613 male general riders	Persian MRBQ (48 items, 6-factor model: Speed Violations, Traffic Errors, Safety Violations, Traffic Violations, Stunts, Control Errors); Linear regression, ANOVA, *t*-test	Major predictors of risky riding include: not having a license, riding daily, riding powerful motorbikes, using mobile phones, hands-free riding, receiving police alerts, and not wearing a helmet.
Sumit et al. (2021). India	N = 300; young riders (university students)	Modified 43-item MRBQ; 5-factor EFA (Traffic errors, Control errors, Stunts, Violations, Protective equipment); Logistic regression	Stunts and violations were significantly associated with near-crashes and fines; protective equipment use was negatively associated with severe crash injury.
Ahmad et al. (2022). Malaysia	N = 184 young riders (university students)	Adapted MRBQ (59 items); 5 factors: Traffic Errors, Speeding, Safety Violations, Safety Equipment, Precautions; Logistic regression analysis of crash predictors	Safety violations increased the risk of crashes, while precautionary behaviors reduced the risk of crashes. Male students had higher rates of crashes and near-miss incidents.
Schreurs et al. (2023). Belgium	560 general motorcyclists	Original 43-item MRBQ; PCA (5-factor solution: speed violations, traffic errors, stunts, protective gear, control errors); Binary logistic regression.	Traffic errors, stunts, younger age, and high exposure to risk are predictors of near-crashes. Speed violations, age, and exposure are factors that predict the amount of fines. Crashes not predicted.
Chouhan et al. (2023). Systematic Review (Global)	N = 17,000 + across 11 studies (2007–2021)	Systematic review and *meta*-analysis of MRBQ-based studies; Factors analyzed included Traffic Errors, Control Errors, Speed Violations, Stunts, and Safety Equipment Use; random-effects model	Speed violations were weakly but significantly associated with self-reported crashes; other MRBQ factors showed no significant predictive value. Age and riding experience were significant demographic predictors.
Pervez et al. (2024). Pakistan	N = 1,344 general motorcyclists	Adapted 48-item MRBQ; EFA (5-factor structure; speeding violations, traffic errors, safety violations, stunts, control errors), multivariate probit for crash, near-crash, and violations	Speeding, traffic errors, and safety violations were predictive of crashes; young, low-income, and unlicensed riders were at the highest risk of being involved in crashes.
Kumar et al. (2024). India	N = 508 young general motorcyclists aged below 25 years	Customized 37-item MRBQ; EFA (5-factor solution: Unmindfulness, Speeding, Violations, Helmet, Road Rage), CFA, SEM	Unmindfulness, poor helmet use, and road rage were predictors of crashes; speeding was not a significant factor.
Sunmud et al. (2024). Thailand	N = 399 middle-aged and older general motorcyclists	Adapted 39-item MRBQ; EFA identified 4-factor structure: speed violations, control errors, traffic errors, safety, CFA	Speed violations had the most substantial factor loadings; control errors included device use; safety items focused on helmet use.

(*continued on next page*)

Table 1 (*continued*)

Authors (Year), Country	Sample (size, population)	Methodology (MRBQ version)	Key Findings
Laphrom et al. (2024). Thailand	N = 2,000 food delivery riders	Modified MRBQ (43 items), HBM (35 items), and 14 work-related items (fatigue, time pressure, aggression); SEM	Risky behaviors were predicted by time pressure, alcohol use, and fatigue; safety motivation was protective.
Setyowati et al. (2024). Indonesia	37 university students	Adapted MRBQ (27 items); factors: Traffic Errors, Control Errors, Speed Violations, Stunts, Safety Equipment.	Traffic violations are marginally associated with riskier behavior, with no significant effects observed for gender, license status, or accident history.
Perego et al. (2024). Tanzania	233 general motorcyclists in Arusha	Adapted MRBQ (35 items); factors: Traffic Errors, Speed Violations, Stunts, Safety Equipment, Control Errors.	High weekly riding hours (avg. 88.7 h) and crash involvement (avg. 1.3 crashes/year). Traffic errors are significantly associated with self-reported crashes.

Note. SEM = Structural Equation Modeling; GLM = Generalized Linear Model; HBM = Health Belief Model.

(2007) reported traffic errors as the strongest correlate of crashes, while Stephens et al. (2017) in Australia identified stunt behaviors as tripling the risk of crashes. Schreurs et al. (2023) demonstrated that near-crashes, rather than actual crashes, were more strongly associated with traffic errors and stunts.

In LMICs, the MRBQ has been customized to reflect local riding environments. Studies from Pakistan (Pervez et al., 2024) introduced a 'safety violations' factor; in Vietnam (Bui et al., 2020), traffic and control errors, along with alcohol violations, were significantly associated with crash outcomes; in India (Kumar et al., 2024), emotional and cognitive states such as unmindfulness and road rage emerged as key predictors. Thai studies (Laphrom et al., 2024; Sunmud et al., 2024) extended the MRBQ to middle-aged, elderly, and delivery riders, identifying work-related stressors as contributors to risky behaviors.

Few MRBQ studies have focused on sub-Saharan Africa. Three studies from Nigeria (Oluwadiya et al., 2020; Sunday, 2010; Sunday & Akintola, 2010) employed adapted MRBQ tools to assess general and commercial riders, identifying predictors such as speed violations and alcohol use. Only one MRBQ-based study (Perego et al., 2024) has been conducted in Tanzania, using a sample of general motorcyclists in Arusha. However, that study did not distinguish commercial MTRs from other rider types, nor did it reflect DSM's political and regulatory environment.

Collectively, these studies underscore both the versatility and limitations of the MRBQ. While it has proven adaptable across various settings, existing African studies are scarce and often lack a focus on commercial MTRs. Additionally, differences in transport regulation, enforcement capacity, and political dynamics, particularly prominent in cities like DSM, suggest that behavioral patterns and crash risks may operate differently than in other LMIC or African urban contexts.

This study builds on the MRBQ literature by tailoring the instrument to the socio-political and infrastructural realities of commercial MTRs in DSM. By examining both behavioral patterns and their association with crash, near-crash, and enforcement outcomes, it contributes much-needed data from a high-risk yet understudied population in sub-Saharan Africa.

3. Methods

3.1. Study design and ethical considerations

This cross-sectional study used a structured, self-administered questionnaire to examine associations between self-reported risky riding behaviors and road safety outcomes among MTRs in DSM, Tanzania. Ethical approval was obtained from the Social-Societal Ethics Committee (SMEC) at Hasselt University (Reference: REC/SMEC/2022–2023/58). Participants gave verbal informed consent, and no personally identifiable information was collected. Data were anonymized to ensure confidentiality.

3.2. Survey instrument

The survey instrument for this study was an adapted version of the MRBQ, initially developed by Elliott et al. (2007). Its relevance for assessing motorcycling-specific risk behaviors is significant, encompassing essential domains such as stunts, balance control, and safety gear usage, which are vital for understanding the risks associated with two-wheeled vehicle use. The MRBQ has been successfully employed in various LMIC settings, as demonstrated in Table 1, supporting its adaptation to the Tanzanian context.

To enhance cultural and contextual relevance, a structured expert panel comprising experienced MTRs, traffic police officers, and road safety practitioners reviewed the original 43-item MRBQ. The panel identified risky riding behaviors inadequately represented in the original MRBQ. Through iterative discussion and consensus, the expert panel proposed nine additional items that reflected prevalent practices in DSM, thereby expanding the questionnaire to 52 items. This expert-driven approach ensured the face and content validity of the added items based on lived experiences and professional judgment.

The newly included items captured localized risky behaviors, such as using a phone while riding (talking or texting); riding against traffic flow; riding in pedestrian or bicycle lanes; riding in bus rapid transit (BRT) lanes; overloading passengers; riding under the influence of alcohol or drugs; modifying exhaust systems to produce loud sounds; maintaining an asymmetric riding posture; dragging the motorcycle stand to create sparks; and riding without protective clothing. The instrument was translated into Swahili and then back-translated into English by independent bilingual translators, resolving discrepancies through consensus. A pilot test with three MTRs evaluated item clarity and flow, resulting in refinements to phrasing and sequencing. The final questionnaire also included demographics, riding experience, crash history, and enforcement encounters.

3.3. Sampling and recruitment

The study targeted MTRs aged 18 and above with at least six months of professional riding experience to ensure adequate familiarity with the riding context in DSM. A minimum required sample size of 384 was calculated using OpenEpi, assuming a finite population of 1,000,000 MTRs in DSM, a 50 % prevalence of risky behaviors (Kiwango et al., 2020), 95 % confidence level, and 5 % margin of error. This sample size was considered adequate to detect meaningful associations. To increase power and allow for subgroup analyses, 463 participants were ultimately included.

Convenience sampling was used, guided by a citywide map of motorcycle taxi stands (commonly referred to as vijiwe in DSM). Formal vijiwe were identified using a registry from SHIVYAMAPIDA (the Federation of Motorcycle Riders' Associations). In contrast, informal vijiwe were reached via direct outreach. Vijiwe leaders facilitated appointments, and walk-in participation was also permitted. Sampling occurred across five municipalities in DSM (Ilala, Temeke, Kinondoni, Ubungo, and Kigamboni) to capture variation in riding environments and operational patterns. Although convenience sampling limits statistical generalizability, it provided broad geographic and occupational representation, enhancing the contextual relevance of the findings.

3.4. Data collection

Data were collected through face-to-face assisted and self-administered surveys (administered via Google Forms) over four weeks in August 2024. Trained data collectors, i.e., transport students fluent in Swahili, administered the survey at various motorcycle taxi stands (vijiwe) across multiple city locations, including urban and *peri*-urban areas in DSM. Participants who preferred digital access were given the survey link. Each survey took approximately 15 min. Participants were compensated with TZS 7,500 (approximately €2.50) to offset opportunity costs. Data collection spanned weekdays and weekends to capture variation in rider activity.

3.5. Data analysis

Data analysis was conducted using IBM SPSS Statistics Version 29.0.1.1. Descriptive statistics summarized the sample's sociodemographic and behavioral characteristics, reporting means and standard deviations for continuous variables and frequencies and percentages for categorical variables. An Exploratory Factor Analysis (EFA) was conducted on the 52 items of the adapted MRBQ using Principal Component Analysis (PCA) with Varimax rotation to identify clusters of correlated variables while maximizing the total variance explained. Varimax rotation enhanced interpretability by simplifying the loading structure. This method is widely recommended in behavioral research for identifying latent dimensions in psychometric instruments (Fabrigar & Wegener, 2011; Tabachnick & Fidell, 2019).

The suitability of the data for factor analysis was assessed using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity (Tabachnick & Fidell, 2019). The KMO statistic, which ranges from 0 to 1, evaluates the proportion of variance among variables that is attributable to underlying factors, with values above 0.8 indicating good sampling adequacy. Bartlett's test determines if the correlation matrix deviates significantly from an identity matrix, suggesting sufficient intercorrelation among variables for factor extraction. Factor retention was guided by the Kaiser criterion (eigenvalue > 1) and scree plot inspection, and further supported by parallel analysis using O'Connor's SPSS syntax (O'Connor, 2000). Items with loadings < 0.40 or cross-loadings > 0.40 were excluded to improve construct clarity (Tabachnick & Fidell, 2019; Taherdoost et al., 2014).

Internal consistency was assessed via Cronbach's alpha (≥ 0.70) and Composite Reliability (CR) (≥ 0.60) (Hair et al., 2019; Henseler et al., 2015). Discriminant validity was assessed using the Fornell-Larcker criterion, requiring the square root of the Average Variance Extracted ($\sqrt{\text{AVE}}$) for each construct to exceed its correlations with other constructs (Fornell & Larcker, 1981). Additionally, Pearson's correlations among latent factors were examined to confirm empirical distinctiveness and theoretical patterns of association, supporting construct validity. A Confirmatory Factor Analysis (CFA) was conducted in IBM SPSS Amos 29 to validate the factor structure from EFA. Model fit was assessed using the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Incremental Fit Index (IFI), with values of 0.95 or higher indicating a good fit. Additional criteria included $\chi 2/\text{df} \leq 3.0$, SRMR ≤ 0.08, and RMSEA ≤ 0.06 (Hu & Bentler, 1999).

Given that the three self-reported road safety outcomes (crash involvement, near-crashes, and traffic fines) were reported by the same individuals, they are likely to be statistically correlated, potentially violating the assumption of uncorrelated residuals in separate binary regressions (Washington et al., 2020). To address the binary nature and potential correlations, a multivariate (trivariate) binary probit model was employed. This approach enables the simultaneous estimation of all three binary outcomes while accounting for correlations in their unobserved determinants, resulting in more efficient and unbiased estimates of predictor effects. Following Washington et al. (2020), the trivariate binary probit model can be specified as:

$$\begin{aligned} Y_{n1}^{*} &= X_{n1}\beta_1 + \varepsilon_{n1} \\ Y_{n2}^{*} &= X_{n2}\beta_2 + \varepsilon_{n2} \text{ Where, } Y_{nj} = \begin{cases} 1 if Y_{nj}^{*} > 0 \\ 0 otherwise \end{cases} \\ Y_{n3}^{*} &= X_{n3}\beta_3 + \varepsilon_{n3} \end{aligned}$$

where, Y_{n1}, Y_{n2}, Y_{n3} represent the observed binary outcomes (crash involvement, near-crash, and traffic fine) for the respondent n, and X_{n1}, X_{n2}, X_{n3} are the corresponding sets of explanatory variables. The error terms (ε_{n1}, ε_{n1}, ε_{n1}) follow a multivariate normal distribution with mean zero and a covariance matrix Σ, allowing for non-zero off-diagonal correlations ($\rho 12, \rho 13, \rho 23$) between the equations. This joint modeling approach effectively captures the interdependent nature of risky riding outcomes, providing a more accurate reflection of real-world decision-making processes.

4. Results

4.1. Sample composition

Table 2 presents the key characteristics of the study participants. Most of these riders were male (98.27 %), reflecting the gendered dominance in Tanzania's bodaboda industry. The average age was 29 years (SD = 5.60), with 64.15 % of the participants falling within the 25–34 age range. Educational levels were low, with only 9.72 % attending college or university, 52.70 % completing secondary education, and 5.4 % having no formal education at all. About half (50.11 %) were married, and 50.54 % owned motorcycles. Most (90.06 %) worked full-time as motorcycle taxi operators, with an average riding experience of 5 years (SD = 3.54). Daily riding exposure was high, with 89.64 % of participants riding between 9 and 16 h daily, and 54.00 % riding daily. Income levels were modest, with 86.39 % earning between TZS 200,000 and TZS 500,000 per month (approx. €65.53 to €163.82), and a mean of 368,990.28 (SD = 147,019.89) (approx. €120.90). Regarding training and licensing, 77.97 % held a valid motorcycle license, and 70.19 % had undergone formal license training. Self-reported safety outcomes revealed significant risk exposure; 66.52 % experienced near-misses, 47.08 % were involved in a crash, and 67.82 % had been fined for traffic offenses in the previous year.

4.2. Descriptive analysis of riding behaviors

Descriptive statistics for all 52 MRBQ items are presented in Table 3. Helmet use was the most consistently practiced safety behavior (M = 4.14), followed by moderate engagement in contextual risky behaviors such as mobile phone use (M = 2.72), riding in unauthorized lanes (M = 2.69), and speeding during off-peak hours (M = 2.57). The low mean scores for stunt behaviors, such as wheelies and dragging the motorcycle stand, suggest that such high-risk displays were relatively rare among participants.

4.3. Factor structure of the adapted MRBQ

4.3.1. Exploratory factor analysis

The EFA was conducted on the 52 items included in the adapted MRBQ. The Kaiser-Meyer-Olkin indicated sampling adequacy (KMO = 0.892). Bartlett's Test of Sphericity was significant ($\chi 2 = 10{,}998.12$, df $= 1326$, $p < 0.001$), confirming the appropriateness of the data for factor analysis. An initial eleven-factor solution explained 60.5 % of the total variance; however, it exhibited significant cross-loadings and lacked conceptual clarity. To refine the structure, a parallel analysis was conducted using the SPSS syntax developed by O'Connor (2000), which supported the retention of six factors, as only six components exceeded the 95th percentile of simulated eigenvalues.

Table 2
Demographic characteristics of participants.

Variable	Description	Frequency	Percent
Age	18 to 24 years	82	17.71
	25 to 34 years	297	64.15
	35 to 44 years	77	16.63
	45 + years	7	1.51
Gender	Male	455	98.27
	Female	8	1.73
Education Level	No formal education	25	5.40
	Primary education	102	22.03
	Secondary education	244	52.70
	Vocational/technical education	47	10.15
	College/university education	45	9.72
Marital Status	Single	203	43.84
	Married	232	50.11
	Divorced/Separated	18	3.89
	Widow/Widower	10	2.16
Dependents	0 dependents	22	5
	1–2 dependents	136	29
	3–4 dependents	186	40
	5 + dependents	119	26
Motorcycle Ownership	Owned outright	234	50.54
	Rent-to-own agreement	146	31.53
	Rent (not to own) agreement	46	9.94
	Financed (paying in installments)	37	7.99
Job Type	Full-time MTR	417	90.06
	Part-time MTR	46	9.94
Riding Experience	Less than one year	8	1.73
	1–2 years	123	26.57
	3–5 years	223	48.16
	6–10 years	77	16.63
	More than ten years	32	6.91
Riding Frequency per Week	3–4 days per week	13	2.81
	5–6 days per week	200	43.20
	Every day	250	54.00
Riding Frequency per Day	4 h to 8 h	28	6.05
	9 to 12 h	170	36.72
	13 to 16 h	245	52.92
	17 + hours	20	4.32
Monthly Income	Less than TZS 200,000 (≈ €66)	12	2.59
	TZS 200,000 − TZS 500,000 (≈ €66–164)	400	86.39
	Above TZS 500,000 (≈ €164 +)	51	11.02
License Status	Yes	361	77.97
	No	102	22.03
Formal License Training	Yes	325	70.19
	No	138	29.81
Road Safety Training	Yes	322	69.55
	No	141	30.45
Near-Crashes in the Past 12 Months	0	155	33.48
	1	136	29.37
	2	91	19.65
	3 or above	81	17.49
Crashes in the Past 12 Months	0	245	52.92
	1	136	29.37
	2	33	7.13
	3 or above	49	10.58
Fined Offences in the Past 12 Months	0	149	32.18
	1	93	20.09
	2	94	20.30
	3 or above	127	27.43
Variable	**Description**	**M**	**S.D.**
Age	Age at the time of the interview	29	5.60
Number of Dependents	Individuals financially supported by the rider	4	2.23
Monthly Income	The rider's average monthly earnings in TZS from operating a motorcycle taxi	368,990.28 (≈ €121.26)	147,019.89 (≈ €48.32)
Riding Experience	The total duration of time, in years, that the rider has been operating a motorcycle taxi	5	3.54
Riding Frequency per Week	The average number of days per week the rider operates the motorcycle taxi	6	0.76
Riding Frequency per Day	The average number of hours per day the rider operates the motorcycle taxi	13	2.41

Note: Euro values are approximate (1 EUR ≈ 3042.71 TZS; BoT, 2025; accessed 01-May-2025).

Through iterative refinement, a more interpretable five-factor structure was identified, ultimately comprising 44 items and explaining 48.20 % of the total variance. Items with factor loadings below 0.40 or with cross-loadings above 0.40 were excluded to enhance interpretability and reliability, consistent with the guidelines set forth by Tabachnick and Fidell (2019). The first factor, labeled Stunts (ST), accounted for 21.70 % of the variance and reflected thrill-seeking and acrobatic riding behaviors. A total of ten items loaded on this factor, but two items, *"ride when you suspect you might be over the legal limit for alcohol" and "miss 'Give Way' signs and narrowly avoid colliding with traffic having the right of way,"* were excluded due to conceptual misfit. The remaining eight items were used to compute the composite Stunts score, which demonstrated good internal consistency (Cronbach's α = 0.863; CR = 0.868).

The second factor, Safety Equipment (SE), explained 11.21 % of the variance, focusing on the utilization of protective gear and visibility-enhancing clothing. All eight items that loaded on this factor were retained in the composite score (α = 0.876; CR = 0.895). The third factor, Traffic Errors (TE), explained 6.99 % of the variance and included behaviors reflecting unintentional errors, lapses, or misjudgments. A total of twelve items loaded on this factor, but one, *"have trouble with your visor or goggles fogging up,"* was excluded due to its mechanical rather than behavioral nature. The final eleven items were used to compute the composite Traffic Errors score (α = 0.827; CR = 0.807).

The fourth factor, Traffic Violations (TV), accounted for 4.65 % of the variance and represented deliberate breaches of traffic laws. While seven items initially loaded on this factor, *"wear no protective clothing"* was excluded due to its ambiguous interpretation. The final composite Traffic Violations score was based on six items (α = 0.768; CR = 0.765). The fifth factor, Contextual Risky Behaviors (CRB), explained 3.66 % of the variance and reflected behaviors driven by local norms and occupational pressures. All seven items that loaded on this factor were retained in the final composite scale (α = 0.756; CR = 0.780).

4.3.2. Descriptive statistics for composite scales

Table 4 presents the mean scores for the five composite scales, all of which show acceptable psychometric properties. Internal consistency ranged from α = 0.756 to 0.876, and composite reliability (CR) ranged from 0.765 to 0.895. Most items loaded above 0.50, supporting convergent validity, while discriminant validity was affirmed by the Fornell-Larcker criterion and inter-factor correlation patterns (see Table 5). Among the risky behavior dimensions, Contextual Risky Behaviors had the highest mean score (M = 2.778, S.D. = 0.820), followed by Traffic Violations (M = 2.285, S.D. = 0.737), Traffic Errors (M = 2.072, S.D. = 0.518), and Stunts, which were least frequent (M = 1.491, S.D. = 0.543). In contrast, Safety Equipment, a protective behavior, had a moderate mean score (M = 2.366, S.D. = 1.026), indicating variable adoption of safety practices among riders.

Table 3
Descriptive statistics of the adapted MRBQ Items.

S/No	MRBQ Items	M	S.D.
*1**	*Wearing a helmet while riding a motorcycle*	*4.14*	*1.692*
*2**	*Overloading passengers*	*3.54*	*1.471*
3	Brake or throttle back when going round a corner or bend.	3.48	1.503
4	Driver deliberately annoys you or puts you at risk.	2.98	1.433
5	Change gear when going around a corner or bend.	2.86	1.622
6	Wear bright/fluorescent clothing.	2.81	1.399
*7**	*Riding on pedestrian or bicycle lanes*	*2.69*	*1.133*
*8**	*Disregard the speed limit late at night or in the early hours of the morning.*	*2.57*	*1.275*
9	Wear a protective jacket (leather or non-leather).	2.52	1.561
10	Wear riding boots.	2.50	1.580
*11**	*Riding on Bus Rapid Transit (BRT) lanes*	*2.49*	*1.423*
12	Ride between two lanes of fast-moving traffic.	2.45	1.199
13	Wear no protective clothing.	2.39	1.453
*14**	*Using a mobile phone while riding a motorcycle (e.g., talking or texting)*	*2.36*	*1.101*
15	Wear gloves.	2.36	1.419
16	Exceed the speed limit on a motorway.	2.34	1.082
17	Attempt to overtake someone that you had not noticed to be signaling a right turn.	2.33	0.898
18	Pull out on to a main road in front of a vehicle that you had not noticed, or whose speed you have misjudged.	2.33	0.938
19	Ride so close to the vehicle in front that it would be difficult to stop in an emergency.	2.25	0.860
20	Not notice someone stepping out from behind a parked vehicle until it is nearly too late.	2.23	0.877
21	Fail to notice or anticipate that another vehicle might pull out in front of you and have difficulty stopping.	2.19	0.901
22	Distracted or preoccupied, you belatedly realize that the vehicle in front has slowed, and you have to brake hard to avoid a collision.	2.12	0.837
23	Fail to notice that pedestrians are crossing when turning into a side street from a main road.	2.12	0.800
24	Queuing to turn left on a main road, you pay such close attention to the main traffic that you nearly hit the vehicle in front.	2.11	0.963
*25**	*Riding against the direction of other vehicles (wrong lane riding).*	*2.11*	*0.935*
26	Wear protective trousers (leather or non-leather).	2.09	1.457
27	Not notice a pedestrian waiting to cross at a zebra crossing or a pelican crossing that has just turned red.	2.08	0.746
28	When riding at the same speed as other traffic, you find it difficult to stop in time when a traffic light has turned against you.	2.08	0.838
29	Use dipped headlights on your motorcycle.	2.06	0.883
30	Race away from traffic lights with the intention of beating the driver/rider next to you.	2.06	1.009
31	Have trouble with your visor or goggles fogging up.	2.01	0.832
32	Exceed the speed limit on a residential road.	1.99	0.841
33	Skid on a wet road or manhole cover.	1.98	0.920
34	Exceed the speed limit on a country/rural road.	1.95	0.985
35	Find that you have difficulty controlling the bike when riding at speed (e.g. steering wobble).	1.93	0.999
36	Miss “Give Way” signs and narrowly avoid colliding with traffic having the right of way.	1.89	0.840
37	Wear body armor (elbow pads, shoulder pads, knee pads, etc.).	1.83	1.199
38	Run wide when going around a corner.	1.83	0.841
39	Open up the throttle and just ‘go for it’ on country roads.	1.82	0.851
40	Wear bright/fluorescent strips/patches on your clothing.	1.81	1.082
41	Unintentionally do a wheel spin.	1.75	0.811
42	Ride so fast into a corner that you scare yourself.	1.74	0.926
43	Wear a leather one-piece suit.	1.69	1.082
44	Pull away too quickly, and your front wheel comes off the road.	1.67	0.797
*45**	*Ride when you suspect you might be over the legal limit for alcohol.*	1.65	0.991
46	Ride so fast into a corner that you feel like you might lose control.	1.57	0.701
47	Riding at speed while deliberately leaning to one side in a stylized or show-off manner.	1.45	0.790
48	Attempt to do, or actually do, a wheelie.	1.44	0.750
49	Get involved in unofficial ‘races’ with other riders or drivers.	1.43	0.729
*50**	*Modifying the exhaust to produce loud, explosive sounds while riding.*	*1.42*	*0.788*
51	Intentionally do a wheel spin.	1.40	0.728
*52**	*Riding a motorcycle while deliberately dragging its stand to create sparks.*	*1.29*	*0.627*

Note: Items marked with * and presented in italics represent context-specific adaptations to the original MRBQ developed by Elliott et al. (2007).

4.3.3. Confirmatory factor analysis

CFA was conducted to validate the five-factor structure from the EFA. The model demonstrated a moderate fit: CMIN/DF = 2.93, RMSEA = 0.065 (90 % CI: 0.061–0.067), PCLOSE = 0.000, CFI = 0.819, TLI = 0.803, GFI = 0.815, and AGFI = 0.788. While the RMSEA and CMIN/DF values indicated a satisfactory model fit, the CFI and TLI indices were slightly below the conventional thresholds of 0.90–0.95. Such moderate values are frequently regarded as acceptable in behavioral and social science research when models include numerous observed variables and correlated latent factors that capture heterogeneous self-reported behaviors (Hair et al., 2019; Marsh et al., 2009). These results reflect the model's complexity rather than misspecification and do not compromise the conceptual coherence of the five-factor structure.

Standardized factor loadings ranged from 0.45 to 0.86, with most items loading above 0.50, supporting good convergence (See Fig. 1). To improve model fit, 14 error covariances were added between conceptually similar items, such as wheel spin and wheelie behaviors under the “Stunts” factor, as well as various protective gear items under “Safety Equipment Use.” All retained items were consistent with their intended latent constructs. Inter-factor correlations ranged from 0.06 to 0.74, with the strongest associations between Traffic Violations and Traffic Errors ($\rho = 0.74$) and between Safety Equipment and Contextual Risky Behaviors ($\rho = 0.64$), indicating meaningful relationships across specific dimensions of riding behavior. Overall, the CFA supported the five-factor model with acceptable structural validity, internal consistency, and theoretical alignment.

4.3.4. Correlation analysis

Pearson correlation coefficients were calculated to examine associations among the five behavior dimensions (Table 5). The strongest correlation was observed between Traffic Errors and Traffic Violations ($r = 0.574$, $p < 0.01$), suggesting that unintentional errors and deliberate rule-breaking behaviors may co-occur in specific riders. Stunt behaviors showed moderate associations with both Traffic Errors ($r = 0.502$) and Traffic Violations ($r = 0.391$), suggesting that thrill-seeking tendencies are related to both forms of risk. In contrast, Safety Equipment had a weak correlation with other risk factors, indicating a distinct behavioral profile. The Fornell-Larcker criterion for discriminant validity was satisfied, with the square roots of AVE values exceeding inter-factor correlations in all cases except Traffic Errors (see Table 5), which exhibited marginal conceptual overlap with Traffic Violations.

4.4. Predictors of crash involvement, near-crashes, and traffic fines

Predictors of crash involvement, near-crash incidents, and traffic fines were examined using a multivariate probit model (see Table 6). The model demonstrated good fit (Wald $\chi^2(96) = 2325.70$, $p < 0.001$), and revealed significant positive correlations among crash, near-crash, and traffic fines outcomes: $\rho = 0.344$ (crash and near-crash), $\rho = 0.334$ (crash and fines), and $\rho = 0.524$ (near-crash and fines), supporting the use of a joint estimation approach. Contextual Risky Behaviors were significantly associated with all three outcomes. Traffic Errors were positively associated with crashes and near-crashes. Stunt behaviors

Table 4
Factor loadings from EFA (varimax with Kaiser normalization).

S/No	Code	Item	Stunts	Safety Equipment	Traffic Errors	Traffic Violations	Contextual Risky Behaviors
51	ST1	Intentionally do a wheel spin.	0.745				
49	ST2	Get involved in unofficial 'races' with other riders or drivers.	0.735				
48	ST3	Attempt to do, or actually do, a wheelie.	0.726				
50	ST4	Modifying the exhaust to produce loud, explosive sounds while riding.	0.726				
47	ST5	Riding at speed while deliberately leaning to one side in a stylized or show-off manner.	0.693				
44	ST6	Pull away too quickly, and your front wheel comes off the road.	0.624				
39	ST7	Open up the throttle and just 'go for it' on country roads.	0.572				
45	*ST8*	*Ride when you suspect you might be over the legal limit for alcohol.*	*0.542*				
52	ST9	Riding a motorcycle while deliberately dragging its stand to create sparks.	0.531				
36	*ST10*	*Miss "Give Way" signs and narrowly avoid colliding with traffic having the right of way.*	*0.419*				
40	SE1	Wear bright/fluorescent strips/patches on your clothing.		0.808			
9	SE2	Wear a protective jacket (leather or non-leather).		0.799			
37	SE3	Wear body armor (elbow pads, shoulder pads, knee pads, etc.).		0.799			
26	SE4	Wear protective trousers (leather or non-leather).		0.778			
10	SE5	Wear riding boots.		0.778			
43	SE6	Wear a leather one-piece suit.		0.736			
1	SE7	Wearing a helmet while riding a motorcycle		0.523			
15	SE8	Wear gloves.		0.479			
21	TE1	Fail to notice or anticipate that another vehicle might pull out in front of you and have difficulty stopping.			0.661		
28	TE2	When riding at the same speed as other traffic, you find it difficult to stop in time when a traffic light has turned against you.			0.643		
22	TE3	Fail to notice that pedestrians are crossing when turning into a side street from a main road.			0.626		
27	TE4	Not notice a pedestrian waiting to cross at a zebra crossing or a pelican crossing that has just turned red.			0.620		
20	TE5	Not notice someone stepping out from behind a parked vehicle until it is nearly too late.			0.544		
38	TE6	Run wide when going around a corner.			0.468		
23	TE7	Distracted or preoccupied, you belatedly realize that the vehicle in front has slowed, and you have to brake hard to avoid a collision.			0.461		
18	TE8	Pull out on to a main road in front of a vehicle that you had not noticed, or whose speed you have misjudged.			0.457		
46	TE9	Ride so fast into a corner that you feel like you might lose control.			0.446		
17	TE10	Attempt to overtake someone that you had not noticed to be signaling a right turn.			0.418		
35	TE11	Find that you have difficulty controlling the bike when riding at speed (e.g. steering wobble).			0.406		
31	*TE12*	*Have trouble with your visor or goggles fogging up.*			*0.400*		
8	TV1	Disregard the speed limit late at night or in the early hours of the morning.				0.671	
12	TV2	Ride between two lanes of fast-moving traffic.				0.656	
32	TV3	Exceed the speed limit on a residential road.				0.632	
7	TV4	Riding on pedestrian or bicycle lanes				0.590	
34	TV5	Exceed the speed limit on a country/rural road.				0.582	
30	TV6	Race away from traffic lights with the intention of beating the driver/rider next to you.				0.416	
13	*TV7*	*Wear no protective clothing.*				*0.400*	
14	CRB1	Using a mobile phone while riding a motorcycle (e.g., talking or texting)					0.727
4	CRB2	Driver deliberately annoys you or puts you at risk.					0.705
2	CRB3	Overloading passengers					0.690
11	CRB4	Riding on Bus Rapid Transit (BRT) lanes					0.653
19	CRB5	Ride so close to the vehicle in front that it would be difficult to stop in an emergency.					0.420
3	CRB6	Brake or throttle-back when going round a corner or bend.					0.419
16	CRB7	Exceed the speed limit on a motorway.					0.402
		M	1.491	2.366	2.072	2.285	2.778
		S.D.	0.543	1.026	0.518	0.737	0.820
		% of Variance	21.697	11.207	6.987	4.647	3.663
		Cronbach's Alpha	0.863	0.876	0.827	0.768	0.756
		Composite Reliability (CR)	0.868	0.895	0.807	0.765	0.780

Note: Italicized factor loadings indicate items that were not included in the computation of the corresponding composite scale despite loading onto the factor. Non-italicized items were retained and used to compute the composite scale.

showed a significant association with only crashes. Notably, Safety Equipment appeared to reduce the likelihood of receiving traffic fines. Traffic Violations did not independently predict any of the three outcomes after adjusting for other variables.

Demographic and socioeconomic factors also influenced the results. Older riders (45 +) reported fewer crashes and fines compared to younger riders (18–24), while those aged 25–44 were less involved in near-crashes, possibly reflecting increased caution or experience. Surprisingly, higher education levels correlated with a greater likelihood of reporting all three safety outcomes, suggesting more awareness or differing attitudes toward reporting. Riders with three to four dependents exhibited higher crash rates, but this effect did not apply to near-crashes or fines. Income also played a role; those earning above TZS 500,000 (≈ €164.37) per month reported more near-crashes and fines.

Table 5
Inter-factor correlations and square roots of AVE.

Factor	Stunts	Safety Equipment	Traffic Errors	Traffic Violations	Contextual Risky Behaviors
Stunts	1				
Safety Equipment	0.070	1			
Traffic Errors	0.502**	0.265**	1		
Traffic Violations	0.391**	0.076	0.574**	1	
Contextual Risky Behaviors	0.140**	0.403**	0.366**	0.440**	1
√AVE	0.673	0.723	0.531	0.597	0.590

Note: ** indicates correlation is significant at the 0.01 level (2-tailed).

Rent-to-own or rental motorcycle users were less likely to report crashes but more likely to report receiving fines, compared to those who owned their motorcycles outright. One possible explanation is that rent-to-own riders may adopt more cautious riding practices to avoid damaging their motorcycles or losing access to a vehicle they are still financing.

Finally, riding exposure and training variables had mixed associations with safety outcomes. Daily riding was associated with a higher likelihood of crash involvement, while longer daily riding hours correlated with reduced crash risk but higher odds of being fined. A lack of formal license training was associated with a higher near-crash risk, and the absence of general motorcycle training was also positively related to near-crash involvement. These findings highlight the complex interplay between behavior, training, and socioeconomic context in shaping road safety risks among MTRs.

5. Discussion

This study examined self-reported risky riding behaviors among MTRs in DSM, Tanzania, using an adapted version of the MRBQ. By validating a locally relevant factor structure and examining associations with crash, near-crash, and enforcement outcomes, the findings contribute new insights into the behavioral profiles of professional riders in an African urban setting and challenge assumptions drawn from MRBQ studies in other contexts.

5.1. Risky riding profiles and local context

The adapted MRBQ revealed a five-factor structure, traffic errors, traffic violations, stunt behaviors, contextual risky behaviors, and safety equipment use, which demonstrated strong internal consistency and conceptual clarity. While partially aligning with MRBQ studies from the UK (Elliott et al., 2007), Turkey (Özkan et al., 2012), and Australia (Stephens et al., 2017), the emergence of a distinct Contextual Risky Behaviors factor underscores the influence of local infrastructure, enforcement, and occupational realities in shaping rider behavior in DSM.

Several risky behaviors, such as mobile phone use, overloading, and limited protective gear usage, are common across LMICs as reported in prior studies in Thailand (Laphrom et al., 2024; Sunmud et al., 2024), Nigeria (Oluwadiya et al., 2020; Sunday, 2010; Sunday & Akintola,

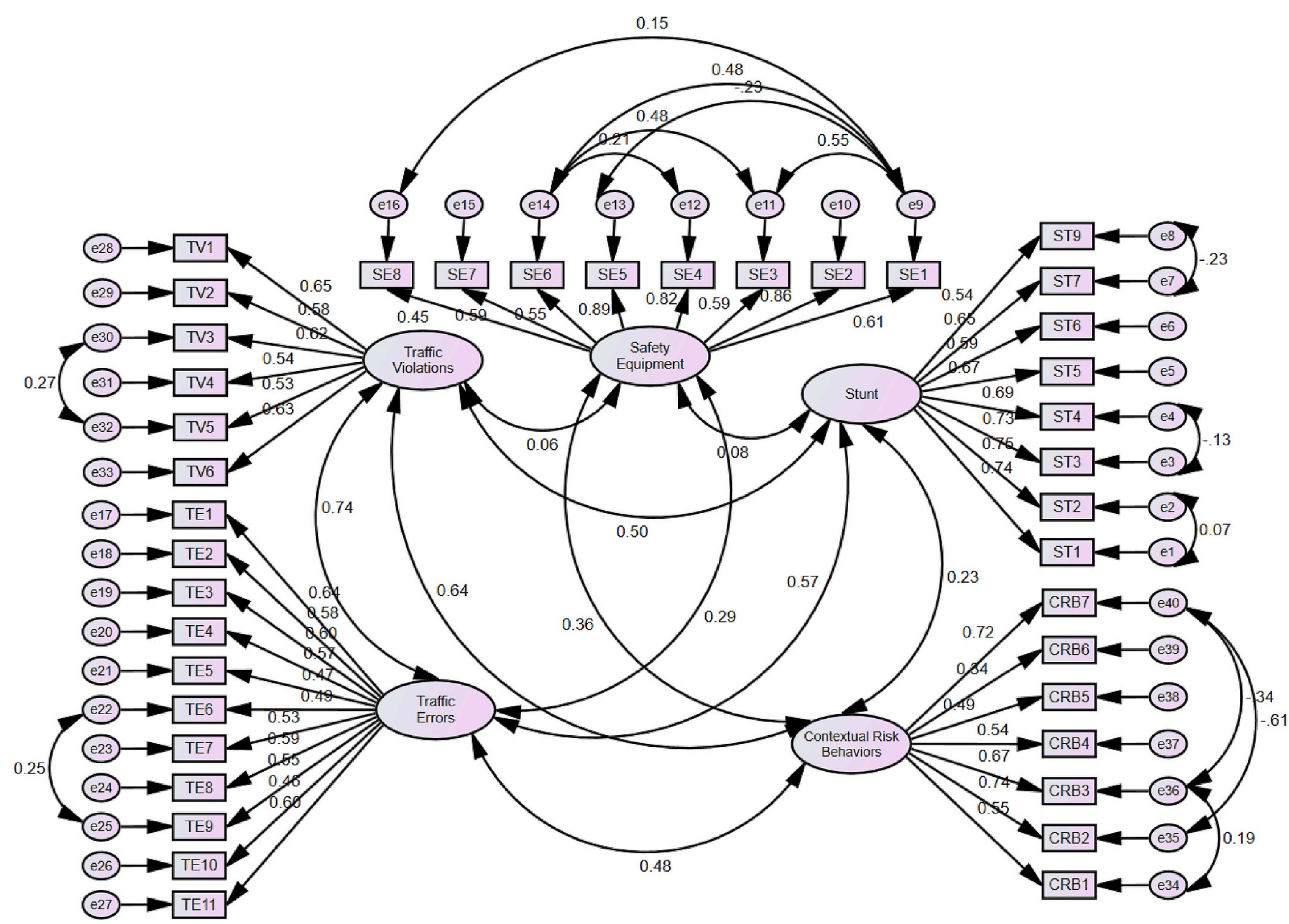

Fig. 1. CFA model of the adapted MRBQ showing standardized loadings and correlated residuals.

Table 6
Predictors of self-reported incidents from the multivariate probit model.

Variable	Category	Crashes (Coef., SE, p)	Near Crashes (Coef., SE, p)	Fined Offenses (Coef., SE, p)
Stunts	–	0.257, 0.129, 0.047 *	–	–
Safety Equipment	–	–	–	−0.158, 0.076, 0.036 *
Traffic Errors	–	–	0.491, 0.154, 0.001 **	–
Traffic Violations	–	–	–	–
Contextual Risky Behaviors	–	0.191, 0.085, 0.025 *	0.333, 0.097, 0.001 **	0.348, 0.098, 0.000 **
Age (Ref. = 18 to 24 years)	25 to 34 years	–	−0.748, 0.217, 0.001 **	–
	35 to 44 years	–	−0.857, 0.300, 0.004 **	−0.662, 0.286, 0.021 *
	45 + years	−4.989, 0.380, 0.000 **	–	−1.783, 0.594, 0.003 **
Education (Ref. = No formal education)	Primary education	–	1.260, 0.377, 0.001 **	1.394, 0.356, 0.000 **
	Secondary education	–	1.472, 0.373, 0.000 **	1.641, 0.351, 0.000 **
	Vocational/ technical education	–	1.385, 0.426, 0.001 **	1.586, 0.402, 0.000 **
	College/ university education	–	1.288, 0.435, 0.003 **	1.465, 0.427, 0.001 **
Dependents (Ref. = 0 dependents)	3–4 dependents	0.793, 0.334, 0.017 *	–	–
	5 + dependents	–	–	–
Income (Ref. = Less than TZS 200,000)	TZS 200,001 – TZS 500,000	–	–	0.681, 0.213, 0.001**
	Above TZS 500,000	–	1.071, 0.351, 0.002 **	1.058, 0.318, 0.001 **
Riding Experience	–	–	–	–
Ownership (Ref. = Owned outright)	Rent-to-own agreement	−0.362, 0.160, 0.024 *	–	−0.412, 0.169, 0.015 *
	Rent (not to own) agreement	–	–	−0.514, 0.247, 0.037 *
Ride Frequency	–	0.390, 0.113, 0.001 **	–	–
Ride Hours	–	−0.090, 0.035, 0.010 *	–	0.076, 0.036, 0.034 *
Formal License Training (Ref. = Yes)	No	–	−0.636, 0.267, 0.017*	–
Formal Training	No	–	0.405, 0.186, 0.029 *	–
Constant	–	−4.210, 0.985, 0.000 **	−3.806, 1.028, 0.000 **	−3.848, 1.053, 0.000 **

Note: Only items with at least one statistically significant variable ($p < 0.05$) are shown. **, and * indicate significance at the 1 % and 5 % levels, respectively. Coef. = Coefficient; SE = Standard Error; Ref = Reference Category.

2010), Colombia (Ospina-Mateus et al., 2021), Southeast Asia (Truong & Nguyen, 2019), and Sub-Saharan Africa (Francis, 2023; Nkonoki & Hamza, 2024), where informal transport systems, economic hardship, and enforcement inconsistencies contribute to normalized risk-taking behaviors. These shared patterns reflect broader LMIC transport challenges and suggest a degree of behavioral convergence among professional riders across urban Global South settings.

In DSM, however, contextual risky behaviors are especially dominant and often serve as occupational adaptations to systemic constraints. Riders frequently operate under high stress, extended working hours, and minimal institutional support (Francis et al., 2023; Luambano, 2020). Behaviors such as riding in pedestrian zones or using Bus Rapid Transit (BRT) lanes are often rationalized as necessary to maximize income due to congestion, inadequate infrastructure, and inconsistent law enforcement. This reflects the normalization of risk-taking as an occupational necessity in a demanding work environment (Kanyama et al., 2004; Kiunsi, 2013; Kiwango et al., 2021; Nguyen et al., 2018).

While similar behaviors have been documented in Southeast Asia (e.g., Truong & Nguyen, 2019) and other parts of Sub-Saharan Africa (e.g., Francis, 2023; Nkonoki & Hamza, 2024), the combination of weak enforcement, political influence, and infrastructural deficits in DSM intensifies these dynamics. For instance, while riders may face penalties for not wearing helmets, other hazardous violations, such as overloading passengers (including children), using a phone (talking/texting) while riding, and riding in BRT lanes, are often overlooked (Kanyama et al., 2004; Kiunsi, 2013).

Moreover, DSM exhibits unique behavioral patterns shaped by its political and infrastructural landscape. The use of BRT lanes by MTRs, for example, is often tolerated due to both road design gaps and selective enforcement (Adeleye et al., 2025). In addition, MTRs' political embeddedness, especially their involvement in electoral campaigns and protests, may create a sense of informal immunity, particularly during election periods (Bourguignon & Wangwe, 2023). Together, these dynamics distinguish DSM from many other LMIC cities and reinforce the contextual nature of rider behavior.

These insights underscore the importance of locally validating and adapting behavioral assessment tools, such as the MRBQ, when applied in diverse cities of the Global South. Although the DSM-adapted MRBQ demonstrated strong psychometric performance, practical application in other cities, such as Accra, Nairobi, or Kampala, will require customization to reflect each city's unique governance patterns, enforcement realities, and occupational pressures.

Safety Equipment use had high internal consistency but low overall prevalence, except for nearly universal helmet use. This pattern mirrors findings from LMICs such as Pakistan, India, and Vietnam, where cost and discomfort deter full gear usage (Bui et al., 2020; Kumar et al., 2024, 2024). DSM's relatively high helmet compliance is likely due to targeted enforcement campaigns and public awareness efforts, including police crackdowns and media engagement. Riders' selective use of protective gear may reflect a calculated balance between safety, affordability, and efficiency.

Stunt behaviors were notably rare among this professional rider population, diverging sharply from MRBQ findings in high-income contexts, where thrill-seeking is more prevalent (Schreurs et al., 2023; Stephens et al., 2017). In DSM, where motorcycles are essential for livelihood, the financial and physical risks of stunting are viewed as unjustifiable, particularly under conditions of intense daily use and income dependence. Similar deterrents due to economic vulnerability have been observed among commercial riders in Nigeria (Oluwadiya et al., 2020; Sunday, 2010) and Indonesia (Susilowati et al., 2018).

Traffic Violations were moderately prevalent but appeared to be adaptive responses rather than deliberate defiance. For example, speeding or riding in opposing lanes may help riders meet passenger demands or navigate deteriorating roads more efficiently. This aligns with studies from Vietnam (Bui et al., 2020), Nigeria (Oguejiofor et al., 2023), India (Chouhan et al., 2021), Kenya (Maru et al., 2024), and

Ghana (Hagan et al., 2021). In DSM, selective enforcement reinforces such behavior; while minor infractions are often penalized, more dangerous violations can go unpunished due to informal arrangements (Issa et al., 2023; Kasavaga et al., 2025).

Traffic Errors, such as poor anticipation or delayed reaction, were moderately frequent and likely reflect the cognitive burden of navigating chaotic roads. Similar findings from India and Colombia suggest that such errors stem from heavy sensory load and the complexity of urban traffic environments (Chouhan et al., 2021; Ospina-Mateus et al., 2021). In the DSM, riders must manage route decisions, customer interactions, and sporadic enforcement simultaneously, which amplifies the risk of cognitive lapses.

The construct structure revealed a modest degree of overlap between Traffic Errors and Traffic Violations. Specifically, the $\sqrt{\text{AVE}}$ for Traffic Errors was slightly lower than its correlation with Traffic Violations, indicating a marginal deviation from the Fornell-Larcker criterion for discriminant validity. This deviation likely reflects the blurred boundaries between unintentional cognitive lapses and deliberate adaptive behaviors in the informal transport context of DSM. In such environments, riders often adapt to systemic inefficiencies, such as congestion, inconsistent enforcement, and chaotic road user behavior, by engaging in actions that straddle the line between error and violation. Notably, a similar pattern was observed in a Thailand-based MRBQ validation study, where speed violations were subsumed under traffic errors during factor analysis (Uttra et al., 2020a), suggesting that construct blending may naturally occur in LMIC contexts where highly dynamic and unpredictable traffic systems shape rider behavior. Despite the observed convergence, both constructs were retained in our model due to their theoretical distinctiveness and their differential associations with safety outcomes observed in the multivariate analysis. The overall model also showed acceptable fit and strong internal consistency, supporting the validity of the retained structure.

5.2. Behavioral predictors of safety outcomes

Traffic Errors and Contextual Risky Behaviors were the most consistent predictors of crash and near-crash involvement. The strength of these associations aligns with findings from Australia and India (Chouhan et al., 2021; Sakashita et al., 2014), though the underlying causes may differ. In DSM, these behaviors are shaped by perceptual overload and occupational stress. In contrast, in HICs, they may reflect distraction or overconfidence. This reinforces the need to interpret behavioral scores in light of contextual constraints. Contextual Risky Behaviors also showed an association with traffic fines, underscoring their high visibility to enforcement. While not inherently more dangerous than other behaviors, their deviation from formal traffic norms — such as using BRT lanes or riding with extra passengers — makes them prime targets for regulation. This mirrors findings from LMICs like Kenya and Nigeria, where informal adaptations often invite punitive enforcement (Maru et al., 2024; Oguejiofor et al., 2023; Oluwadiya et al., 2020).

Surprisingly, Traffic Violations did not significantly correlate with crashes, near-crashes, or fines as seen in other MRBQ studies (Chouhan et al., 2023; Motevalian et al., 2011; Setyowati et al., 2024). This may be due to their normalization in DSM's traffic culture, where even lawful riders regularly commit minor violations. As such, these behaviors may lack predictive power precisely because they are widespread and weakly sanctioned. A similar saturation effect has been suggested in other low-enforcement settings (Francis, 2023). Stunt behaviors were associated with crash involvement, but not with near-crashes or fines. This indicates that when stunts are attempted, they carry a high risk of injury; however, their infrequency and covert nature reduce their association with minor incidents or enforcement. The finding is consistent with the global literature (Ospina-Mateus et al., 2021; Özkan et al., 2012; Schreurs et al., 2023; Sumit et al., 2021) but highlights the specific role stunts play in high-severity, low-frequency risk among commercial riders.

An unexpected result was the positive association between education and all three safety outcomes. Educated riders may operate in busier areas or take more initiative in navigating complex road environments, thereby increasing their risk exposure. Their increased awareness may also prompt more accurate self-reporting. Alternatively, visible indicators of compliance, such as proper attire or new motorcycles, may attract more police scrutiny. This pattern aligns with earlier DSM-based findings (Francis et al., 2023; Kiwango et al., 2024) and challenges the assumption that education always reduces traffic risk (Olivia & Ani, 2024).

Exposure showed a dual pattern: riding more days was associated with an increased crash risk, while riding more hours per day was linked to a reduced crash risk. This may reflect a survivor bias, where only the most skilled or cautious riders persist in high-hour roles. Alternatively, riders with more hours may avoid risky shortcuts and instead adopt more stable, experienced patterns of behavior. These explanations align with studies on occupational driving experience and hazard anticipation (Crundall et al., 2013; Jakobsen et al., 2023). Lastly, formal training was associated with a lower incidence of near-crashes. This supports training as a protective intervention, especially for hazard perception and emergency response. As many MTRs in DSM lack formal instruction, structured training programs offer a tangible policy opportunity. Similar conclusions have been drawn in Indian and Vietnamese rider safety studies (Chouhan et al., 2024; Sumit et al., 2021).

Taken together, these findings highlight that risky riding behaviors among MTRs in DSM are shaped as much by systemic constraints as by individual choices. Understanding these behaviors through a contextual lens is essential for developing effective and equitable safety interventions. The adapted MRBQ offers a validated tool to inform such efforts by capturing the realities of urban motorcycle transport in Tanzania.

6. Practical recommendations

Improving road safety among MTRs in DSM requires a coordinated approach that addresses rider behavior, environmental risks, and institutional capacity. This study highlights three key areas for action.

Strengthening rider skills through cognitive and behavioral training is essential. Programs should focus on hazard anticipation, attention control, and decision-making skills linked to reduced crash risk (Forsman et al., 2022; Mwebesa et al., 2021). Affordable technologies, such as simulators and advanced rider assistance systems (ARAS), including blind spot alerts and lane departure warnings, can reinforce learning and help prevent errors (Ait-Moula et al., 2024; Aleksa et al., 2024; Beanland et al., 2013). In parallel, behavior change campaigns informed by the Theory of Planned Behavior (Ajzen, 1991) and the Health Belief Model (Rosenstock, 1974) can help shift perceptions and promote safer norms, particularly among younger riders (Mazaheri et al., 2022; Razmara et al., 2018b).

Creating a safer operating environment involves improving infrastructure and ensuring access to safety equipment. Upgrades such as dedicated motorcycle lanes, clear signage, and self-explanatory roads can reduce the need for risky maneuvers in congested spaces (Chouhan et al., 2024). The adoption of protective gear, such as jackets, gloves, and reflective clothing, can be supported through subsidies and partnerships with NGOs and manufacturers, especially when the gear is tailored to the local climate (Latonero et al., 2024). Enforcement efforts should be more consistent and data-driven, utilizing tools such as helmet detection systems and speed cameras to target high-risk behaviors and mitigate bias (Nzuchi et al., 2022).

Sustainable improvement depends on collaboration across sectors. Traffic police, transport regulators, urban planners, rider associations, NGOs, and private partners must coordinate under a Safe System approach tailored to local realities. Given the occupational need for connectivity and safer communication alternatives, such as hands-free devices, their promotion rather than restriction should be considered, as demonstrated in contexts like Indonesia and Vietnam (Divall et al., 2020). Interventions that are co-designed with riders and grounded in local evidence are more likely to be adopted and sustained over time (Labbo et al., 2024; Usami et al., 2021).

7. Limitations and future research

This study presents several limitations that should be considered when interpreting its findings, while also highlighting areas for future research and refinement of the adapted MRBQ. Reliance on self-reported data may introduce potential for recall or social desirability bias (Latkin et al., 2017), which may affect the accuracy of reported behaviors and outcomes. Although local-language administration and anonymity may have mitigated this risk, future studies should incorporate objective data sources, such as crash records, enforcement data, or GPS tracking, to validate self-reported measures.

The cross-sectional design limits causal interpretations of the observed associations between behaviors and safety outcomes. Longitudinal studies would offer stronger insights into how behavioral changes over time influence crash risk, near-crashes, and enforcement encounters (Brutus et al., 2012).

While all 43 original MRBQ items were retained to ensure theoretical coherence and comparability, several had low mean scores in this setting, particularly those related to stunt behaviors and the use of rare safety gears, such as a one-piece suit. Future adaptations of the tool should consider whether such items remain relevant or should be revised, dropped, or replaced with more locally meaningful indicators.

Due to the mobile and informal nature of MTR operations in DSM, convenience sampling was used. Efforts were made to include riders from diverse districts; however, the non-probability sampling approach may limit the generalizability of the findings. Future research may benefit from probability-based or respondent-driven sampling strategies to enhance representativeness and external validity.

Although the CFA supported the five-factor structure, overall model fit was moderate. Several correlated error terms were introduced to improve model performance, guided by theoretical and empirical considerations. Further refinement of the factor structure and testing across varied LMIC settings is recommended.

Additionally, although the newly developed MRBQ items were derived through a rigorous expert panel review process, they were not subjected to a formal validation technique such as the Index of Item-Objective Congruence (IOC). While the expert input ensured contextual and conceptual relevance, the absence of a structured content validation method may limit the ability to assess the quantitative content validity of the added items. It should be considered in future refinement efforts.

Despite these limitations, the study offers valuable insights into risky riding in an under-researched African urban context. It provides a foundation for refining behavioral tools and enhancing road safety interventions in LMICs.

8. Conclusion

This study offers important insights into the nature, prevalence, and consequences of risky riding behaviors among MTRs in DSM, Tanzania. By adapting and extending the MRBQ, the research captured both globally recognized behaviors and locally embedded practices shaped by infrastructural, economic, and occupational conditions. The five-factor structure comprising traffic errors, contextual risky behaviors, traffic violations, stunts, and safety equipment use was established through exploratory and confirmatory factor analyses. These dimensions showed strong internal reliability and contextual relevance, reflecting the unique pressures faced by riders in the LMIC urban environment. The study also demonstrated associations between self-reported riding behaviors and safety outcomes, supporting the construct validity of the adapted MRBQ. Traffic errors and contextually risky behaviors were significantly associated with crash involvement, near-misses, and fines, highlighting their importance in understanding rider safety. Conversely, behaviors such as stunt riding, which are often linked to a high crash risk in other populations, showed weaker or unexpected associations in this professional cohort. Notably, traffic violations did not significantly predict any safety outcome, suggesting that such behaviors may be normalized adaptations to environmental and occupational constraints rather than indicators of deliberate risk-taking.

These findings underscore the value of interpreting rider behavior through a localized, systems-aware lens. Addressing MTR safety in DSM will require an integrated approach that combines behavior-focused strategies with broader structural reforms, such as improved road infrastructure, consistent enforcement, and access to affordable safety equipment. The adapted MRBQ offers a validated tool for supporting these efforts, with potential applications in future research, monitoring, and policy development. Further refinement and longitudinal validation may enhance its utility across similar urban transport settings in LMICs.

9. Declaration of Generative AI Use

During the preparation of this work, the authors used ChatGPT (OpenAI) and Grammarly Premium to assist with language refinement, grammar checking, and stylistic consistency. After using these tools, the authors reviewed and edited all content manually and take full responsibility for the final version of the manuscript.

CRediT authorship contribution statement

Katondo Salvatory Nambiza: Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **An Neven:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Wilfred Gordian Kazaura:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Muhammad Wisal Khattak:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Kris Brijs:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Funding

This research was funded by VLIR-UOS (Belgium) through the Institutional University Cooperation (IUC) partnership between Hasselt University (Belgium) and Ardhi University (Tanzania) under Grant ID: TZ2022IUC042A104.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors express their sincere appreciation to the motorcycle taxi riders (MTRs) for their participation and to the research assistants who supported the data collection process. The team further acknowledges the institutional support provided by Ardhi University and Hasselt University, facilitated through the VLIR-UOS Institutional University Cooperation (IUC) partnership between the two universities.

Data availability

Data will be made available on request.

References

Adeleye, B.M., Popoola, A.A., Stephano, N., 2025. Assessment of the attitudinal behaviour of Boda Boda Riders in Dar es Salaam, Tanzania. Environ. Technol. Sci. J. 16 (1), 1. https://doi.org/10.4314/etsj.v16i1.26.

Ahmad, N. S., Karuppiah, K., How, V., Md Isa, M. H., & K. C. Mani, K. (2022). Risk riding behaviours of young motorcyclists among students in Universiti Putra Malaysia, Serdang, Selangor. *Universiti Putra Malaysia Press*, *18*(suppl.5), Article suppl.5. http://psasir.upm.edu.my/id/eprint/103112.

Ait-Moula, A., Riahi, E., Serre, T., 2024. Effect of advanced rider assistance system on powered two wheelers crashes. Heliyon 10 (4), e26031. https://doi.org/10.1016/j.heliyon.2024.e26031.

Ajzen, I., 1991. The theory of planned behavior. Organ. Behav. Hum. Decis. Process. 50 (2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T.

Aleksa, M., Schaub, A., Erdelean, I., Wittmann, S., Soteropoulos, A., Fürdös, A., 2024. Impact analysis of advanced driver assistance systems (ADAS) regarding road safety – computing reduction potentials. Eur. Transp. Res. Rev. 16 (1), 39. https://doi.org/10.1186/s12544-024-00654-0.

Beanland, V., Lenné, M.G., Fuessl, E., Oberlader, M., Joshi, S., Bellet, T., Banet, A., Rößger, L., Leden, L., Spyropoulou, I., Yannis, G., Roebroeck, H., Carvalhais, J., Underwood, G., 2013. Acceptability of rider assistive systems for powered two-wheelers. Transport. Res. F: Traffic Psychol. Behav. 19, 63–76. https://doi.org/10.1016/j.trf.2013.03.003.

BoT. (2025). *Exchange Rates*. Bank of Tanzania. https://www.bot.go.tz/exchangerate/excrates.

Bourguignon, F., & Wangwe, S. M. (Eds.). (2023). Five Critical Institutional Areas for Tanzania's Development. In *State and Business in Tanzania's Development: The Institutional Diagnostic Project* (pp. 95–312). Cambridge University Press. https://doi.org/10.1017/9781009285803.007.

Brutus, S., Aguinis, H., Wassmer, U., 2012. Self-reported limitations and future directions in scholarly reports: analysis and recommendations. J. Manag. 39 (1), 48–75. https://doi.org/10.1177/0149206312455245.

Bui, H.T., Saadi, I., Cools, M., 2020. Investigating on-road crash risk and traffic offences in Vietnam using the motorcycle rider behaviour questionnaire (MRBQ). Saf. Sci. 130. https://doi.org/10.1016/j.ssci.2020.104868.

Cholo, W., Odero, W., & Ogendia, J. (2023). *The Burden of Motorcycle Crash Injuries on the Public HealthSystem in Kisumu City, Kenya*. https://doi.org/10.9745/GHSP-D-22-00197.

Chouhan, S.S., Kathuria, A., Chalumuri, R.S., 2024. Powered two-wheeler riding behavior and strategies to improve safety: a review. J. Traffic Transp. Eng. (English Edition). https://doi.org/10.1016/j.jtte.2024.03.006.

Chouhan, S.S., Kathuria, A., Sekhar, C.R., 2021. Examining risky riding behavior in India using Motorcycle rider behavior questionnaire. Accid. Anal. Prev. 160, C7–106312. https://doi.org/10.1016/j.aap.2021.106312.

Chouhan, S.S., Kathuria, A., Sekhar, C.R., 2023. The motorcycle rider behaviour questionnaire as a predictor of crashes: a systematic review and meta-analysis. IATSS Res. 47 (1), 61–72. https://doi.org/10.1016/j.iatssr.2023.01.004.

Crundall, D., van Loon, E., Stedmon, A.W., Crundall, E., 2013. Motorcycling experience and hazard perception. Accid. Anal. Prev. 50, 456–464. https://doi.org/10.1016/j.aap.2012.05.021.

Divall, D., Kureya, T., Bishop, T., Barber, C., Green, C., Clark, S., 2020. The potential role of mobile phone technology in rural motorcycle and three-wheeler taxi services in Africa. Transp. Plan. Technol. 44 (1), 30–44. https://doi.org/10.1080/03081060.2020.1851446.

Ehebrecht, D., Heinrichs, D., Lenz, B., 2018. Motorcycle-taxis in sub-Saharan Africa: current knowledge, implications for the debate on "informal" transport and research needs. J. Transp. Geogr. 69, 242–256. https://doi.org/10.1016/j.jtrangeo.2018.05.006.

Elliott, M.A., Baughan, C.J., Sexton, B.F., 2007. Errors and violations in relation to motorcyclists' crash risk. Accid. Anal. Prev. 39 (3), 491–499. https://doi.org/10.1016/j.aap.2006.08.012.

Fabrigar, L. R., & Wegener, D. T. (2011). Implementing and Interpreting Exploratory Factor Analysis. In L. R. Fabrigar & D. T. Wegener (Eds.), *Exploratory Factor Analysis* (p. 0). Oxford University Press. https://doi.org/10.1093/acprof:osobl/9780199734177.003.0005.

Fornell, C., Larcker, D.F., 1981. Evaluating structural equation models with unobservable variables and measurement error. J. Mark. Res. 18 (1), 39–50. https://doi.org/10.2307/3151312.

Forsman, Å., Jansson, J., Sonja, F., Nuruzzaman, R., Skogsmo, I., & Anna Vadeby. (2022). Riding in a safe system: Outcome from an international workshop on PTW safety. *Road Safety on Five Continents – RS5C*. 19th International Conference Road Safety on Five Continents (RS5C). Grapevine, Texas, USA. Held October 10–12, 2022, Grapevine, Texas, USA. https://vti.diva-portal.org/smash/record.jsf?pid=diva2%3A1709051&utm_source=chatgpt.com&dswid=2158.

Francis, F. (2023). *Risk factors of road traffic injuries among motorcyclists in Dar es Salaam, Tanzania*. https://trid.trb.org/View/2344829.

Francis, F., Möller, J., Moshiro, C., Kiwango, G., Yngve, B.H., Hasselberg, M., 2023. Associations and mediators between types of motorcycle ownership and road traffic injuries among motorcycle taxi drivers in Dar es Salaam. Tanzania. Safety Science 162, 106094. https://doi.org/10.1016/j.ssci.2023.106094.

Gupta, R., Hertzke, P., Lath, V., & Vig, G. (2023, August 17). *The real global EV buzz comes on two wheels*. https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/the-real-global-ev-buzz-comes-on-two-wheels?utm_source=chatgpt.com#/.

Hagan, D., Tarkang, E.E., Aku, F.Y., 2021. Compliance of commercial motorcycle riders with road safety regulations in a peri-urban town of Ghana. PLoS One 16 (3), e0246965. https://doi.org/10.1371/journal.pone.0246965.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage.

Henseler, J., Ringle, C.M., Sarstedt, M., 2015. A new criterion for assessing discriminant validity in variance-based structural equation modeling. J. Acad. Mark. Sci. 43 (1), 115–135. https://doi.org/10.1007/s11747-014-0403-8.

Hu, L., Bentler, P.M., 1999. Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. Struct. Equ. Model. Multidiscip. J. 6 (1), 1–55. https://doi.org/10.1080/10705519909540118.

Ibrahim, U., Msumanje, G., Manda, A., 2023. Decongesting urban areas through implementation of soft transportation policies encouraging public transport usage: explaining critical success factors from commuters' experience. African J. Acc. Soc. Sci. Stud. 5 (1). https://doi.org/10.64717/ajass.v5i1.151.

Issa, I., Nyange, E., Mubarack, K., & Munishi, E. (2023). *Stakeholder's Intervention in Reducing Crime Threat Among Motorcycle Taxi Riding Operators in Dar es Salaam, Tanzania* (pp. 1064–1076). https://doi.org/10.1007/978-3-031-25998-2_82.

Jakobsen, M.D., Glies Vincents Seeberg, K., Møller, M., Kines, P., Jørgensen, P., Malchow-Møller, L., Andersen, A.B., Andersen, L.L., 2023. Influence of occupational risk factors for road traffic crashes among professional drivers: systematic review. Transp. Rev. 43 (3), 533–563. https://doi.org/10.1080/01441647.2022.2132314.

Kanyama, A., Carlsson-Kanyama, A., & Lindén, A.-L. (2004). *Public Transport in Dar-es-Salaam, Tanzania*. (No. Dnr 1123; FOI MEMO, p. 175). https://portal.research.lu.se/en/publications/public-transport-in-dar-es-salaam-tanzania/.

Kasavaga, F., Massawe, L.N., Nyaki, P., 2025. Riding tendencies contributing to emergence of accidents in commercial motorcycles and their associated factors: case of Dar es Salaam city. Tanzania. Open Access Library Journal 12 (4), 4. https://doi.org/10.4236/oalib.1113169.

Kiunsi, R.B., 2013. A review of traffic congestion in Dar es Salaam city from the physical planning perspective. J. Sustain. Dev. 6 (2). https://doi.org/10.5539/jsd.v6n2p94.

Kiwango, G., Francis, F., Moshiro, C., Möller, J., Hasselberg, M., 2021. Association between alcohol consumption, marijuana use and road traffic injuries among commercial motorcycle riders: a population-based, case-control study in Dares Salaam Tanzania. Accid. Anal. Prev. 160, 106325. https://doi.org/10.1016/j.aap.2021.106325.

Kiwango, G., Katopola, D., Francis, F., Möller, J., Hasselberg, M., 2024. A systematic review of risk factors associated with road traffic crashes and injuries among commercial motorcycle drivers. Int. J. Inj. Contr. Saf. Promot. 31 (2), 332–345. https://doi.org/10.1080/17457300.2024.2319628.

Kumar, A., Singh, S., Hussain, S., Bandyopadhyaya, R., Bandyopadhyaya, V., 2024. Identifying factors causing motorcycle crashes among young adults in india using modified motorcycle rider behavior questionnaire. J. Instit. Eng. (India): Series A 105 (1), 91–104. https://doi.org/10.1007/s40030-023-00776-z.

Labbo, M.S., Qu, L., Xu, C., Bai, W., Ayele Atumo, E., Jiang, X., 2024. Understanding risky driving behaviors among young novice drivers in Nigeria: a latent class analysis coupled with association rule mining approach. Accid. Anal. Prev. 200, 107557. https://doi.org/10.1016/j.aap.2024.107557.

Laphrom, W., Champahom, T., Se, C., Nanthawong, S., Wisutwattanasak, P., Ratanavaraha, V., Jomnonkwao, S., 2024. Assessing risky riding behaviors among food delivery motorcyclists in thailand: insights from the motorcycle rider behavior questionnaire and health belief model. Logistics 8 (4), 4. https://doi.org/10.3390/logistics8040125.

Latkin, C.A., Edwards, C., Davey-Rothwell, M.A., Tobin, K.E., 2017. The relationship between social desirability bias and self-reports of health, substance use, and social network factors among urban substance users in Baltimore, Maryland. Addict. Behav. 73, 133–136. https://doi.org/10.1016/j.addbeh.2017.05.005.

Latonero, G.S., Kamid, S., Gaspay, S.M.A., Brides, C.M., 2024. Enhancing_motorcycle_safety_challenges_strategies_and_research_priorities_insights_from_road_Safety_Summit_Workshop_with_Motorcycle_Groups. ResearchGate. https://www.researchgate.net/publication/384117787_Enhancing_Motorcycle_safety_Challenges_Strategies_and_Research_Priorities_Insights_from_Road_Safety_Summit_Workshop_with_Motorcycle_Groups.

Luambano, H., 2020. Operating practice of commercial motorcycle taxis in Dar Es Salaam City: challenges and opportunities. J. Soc. Admin. Sci. 7 (2), 2. https://doi.org/10.1453/jsas.v7i2.2055.

Malima, W., 2024. Police strengthen measures to control traffic rules violation. Daily News. https://dailynews.co.tz/police-strengthen-measures-to-control-traffic-rules-violation/.

Marsh, H. W., Hau, K.-T., & Wen, Z. (2009). *In Search of Golden Rules: Comment on Hypothesis-Testing Approaches to Setting Cutoff Values for Fit Indexes and Dangers in Overgeneralizing Hu and Bentler's (1999) Findings*. 320–341. https://doi.org/10.1207/s15328007sem1103_2.

Maru, M., Osero, J., Kimani, H., 2024. Assessing the main risk traits associated with motorcycle accidents among the motorcycle riders in Kiambu County, Kenya. Journal of Medicine, Nursing & Public Health 7 (2). https://doi.org/10.53819/81018102t2421.

Mazaheri, M., Rezai-Rad, M., & Pelarak, F. (2022). *Strategies to reduce road traffic injuries among motorcyclists in Dezful, Iran: Stressing on legal and environmental factors*. https://doi.org/10.5249/jivr.v14i1.1696.

Motevalian, S.A., Asadi-Lari, M., Rahimi, H., Eftekhar, M., 2011. Validation of a persian version of motorcycle rider behavior questionnaire. Annals of Advances in Automotive Medicine / Annual Scientific Conference 55, 91–98. https://pmc.ncbi.nlm.nih.gov/articles/PMC3256814/.

Mwebesa, M.E., Chou, C.-C., Yoh, K., Doi, K., 2021. A cross-sector framework to boost the sustainable implementation of integrated transport and spatial strategies to improve safety and mobility of moto-taxi riders. Front. Sustainable Cities 3, 775011. https://doi.org/10.3389/frsc.2021.775011.

Nguyen, T., Vissoci, J.R.N., Joelson, T., Pesambili, M., Haglund, M., Gerardo, C.J., Mvungi, M., Staton, C.A., 2018. Injury prevalence and safety habits of boda boda drivers in Moshi, Tanzania: a mixed methods study. PLoS One 13 (11), e0207570. https://doi.org/10.1371/journal.pone.0207570.

Nkonoki, E., Hamza, V., 2024. A qualitative assessment of the role of mobile phone technology in enhancing motorcycle taxi services in Dar es Salaam Tanzania. Transp. Plann. Technol. 1–17. https://doi.org/10.1080/03081060.2024.2384530.

Nzuchi, J.S., Ngoma, S.J., Meshi, E.B., 2022. Commercial motorcyclists and road safety measures compliance. a case study of Dodoma city, central Tanzania. Heliyon 8 (8), e10297. https://doi.org/10.1016/j.heliyon.2022.e10297.

O'Connor, B.P., 2000. SPSS and BAS programs for determining the number of components using parallel analysis and Velicer's MAP test. Behav Res. Methods, Instrum., Comput. 32 (3), 396–402. https://doi.org/10.3758/BF03200807.

Oguejiofor, B.B., Omotosho, A., Abioye, K.M., Alabi, A.M., Oguntoyinbo, F.N., Daraojimba, A.I., Daraojimba, C., 2023. A review on data-driven regulatory compliance in Nigeria. Int. J. Appl. Res. Soc. Sci. 5 (8), 231–243. https://doi.org/10.51594/ijarss.v5i8.571.

Olivia, F., Ani, L.S., 2024. Factors related to traffic accidents among online motorcycle taxi riders in Bekasi. Indones. J. Occup. Saf. Health 13 (1), 1. https://doi.org/10.20473/ijosh.v13i1.2024.65-73.

Oluwadiya, K., Ogunlusi, J., Yusuf, B., 2020. The_validation_of_the_Motorcycle_Rider_Behaviour_Questionnaire_among_Nigerian_motorcycle_taxi_riders. Nigerian Stethoscope 2 (1), 1. https://www.researchgate.net/publication/363090082_The_validation_of_the_Motorcycle_Rider_Behaviour_Questionnaire_among_Nigerian_motorcycle_taxi_riders.

Ospina-Mateus, H., Jiménez, L.Q., López-Valdés, F.J., 2021. The rider behavior questionnaire to explore associations of motorcycle taxi crashes in Cartagena (Colombia). Traffic Inj. Prev. 22 (sup1), S99–S103. https://doi.org/10.1080/15389588.2021.1970749.

Özkan, T., Lajunen, T., Doğruyol, B., Yıldırım, Z., Çoymak, A., 2012. Motorcycle accidents, rider behaviour, and psychological models. Accid. Anal. Prev. 49, 124–132. https://doi.org/10.1016/j.aap.2011.03.009.

Perego, P., Biassoni, F., Mashingo, P., Siebert, F.W., 2024. Motorcycle rider behavior in Tanzania, identifying risk factors using an online survey. Inj. Prev. 30 (Suppl 1), A12–A. https://doi.org/10.1136/injuryprev-2024-SAFETY.30.

Pervez, A., Lee, J.J., Ullah, W., Han, C., Hussain, M., Lee, C., 2024. Risky riding behaviors among motorcyclists and self-reported safety events in Pakistan. Transport. Res. F: Traffic Psychol. Behav. 105, 350–367. https://doi.org/10.1016/j.trf.2024.07.016.

Pervez, A., Mao, S., Lee, J.J., Hussain, M., 2025a. Young motorcyclists' behavior analysis in Pakistan based on modified motorcycle rider behavior questionnaire (MRBQ). Accid. Anal. Prev. 211, 107873. https://doi.org/10.1016/j.aap.2024.107873.

Razmara, A., Aghamolaei, T., Madani, A., Hosseini, Z., Zare, S., 2018b. Prediction of safe driving Behaviours based on health belief model: the case of taxi drivers in Bandar Abbas. Iran. BMC Public Health 18 (1), 380. https://doi.org/10.1186/s12889-018-5300-5.

Rosenstock, I.M., 1974. Historical origins of the health belief model. Health Educ. Monogr. 2 (4), 328–335. https://doi.org/10.1177/109019817400200403.

Sakashita, C., Senserrick, T., Lo, S., Boufous, S., De Rome, L., Ivers, R., 2014. The motorcycle rider behavior questionnaire: psychometric properties and application amongst novice riders in Australia. Transport. Res. F: Traffic Psychol. Behav. 22, 126–139. https://doi.org/10.1016/j.trf.2013.10.005.

Schreurs, K.V., Ross, V., Brijs, K., 2023. Investigating the relationship between self-reported (near) crashes, fined traffic offences, and risky riding behaviours among flemish motorcyclists using the motorcycle rider behaviour questionnaire. Transp. Res. Part F-Traffic Psychol. Behav. 98, 337–353. https://doi.org/10.1016/j.trf.2023.10.002.

Setoodehzadeh, F., Ansari-Moghaddam, A., Okati-Aliabad, H., Khammarnia, M., Mohammadi, M., 2021. Self-reported motorcycle riding behavior in Southeast of Iran. Health Scope 10 (3), 3. https://doi.org/10.5812/jhealthscope.116025.

Setyowati, D.L., Setyaningsih, Y., Suryawati, C., Lestantyo, D., 2024. Assessment of risky riding behaviors using the motorcycle rider behavior questionnaire (MRBQ) among university students. The Open Public Health Journal 17 (1), e18749445281252. https://doi.org/10.2174/0118749445281252240316204804.

Stephens, A.N., Brown, J., de Rome, L., Baldock, M.R.J., Fernandes, R., Fitzharris, M., 2017. The relationship between motorcycle rider behaviour questionnaire scores and crashes for riders in Australia. Accid. Anal. Prev. 102, 202–212. https://doi.org/10.1016/j.aap.2017.03.007.

Sumit, K., Ross, V., Brijs, K., Wets, G., Ruiter, R.A.C., 2021. Risky motorcycle riding behaviour among young riders in Manipal. India. BMC Public Health 21 (1), 1954. https://doi.org/10.1186/s12889-021-11899-y.

Sunday, O.K., 2010. The performance of the motorcycle rider behaviour questionnaire among commercial motorcycle riders in Nigeria. Inj. Prev. 16, A194–A. https://doi.org/10.1136/ip.2010.029215.691.

Sunday, O. K., & Akintola, L. (2010). *The Motorcycle Rider Behaviour Questionnaire (MRBQ) and Commercial Motorcycle Riders in Nigeria*. https://doi.org/10.4324/9781003577973.

Sunmud, S., Arreeras, T., Phonsitthangkun, S., Prommakhot, S., Sititvangkul, K., 2024. Examining risky riding behaviors: insights from a questionnaire survey with middle-aged and older motorcyclists in Thailand. Safety 10 (2), 48. https://doi.org/10.3390/safety10020048.

Susilowati, I.H., Nurhafizhah, T., Maulana, A., Habibullah, M.F., Sunukanto, W.S., Hastiti, L.R., Wirawan, M., 2018. Safety risk factors amongst online motorcycle taxi drivers who provide public transportation in depok, Indonesia. Indian J. Public Health Res. Dev. 9 (10), 578. https://doi.org/10.5958/0976-5506.2018.01408.0.

Tabachnick, B. G., & Fidell, L. S. (2019). *Using multivariate statistics* (Seventh edition). Pearson. https://www.pearson.com/en-us/subject-catalog/p/using-multivariate-statistics/P200000003097/9780137526543.

Taherdoost, H., Sahibuddin, S., & Jalaliyoon, N. (2014). Exploratory Factor Analysis; Concepts and Theory. In J. Balicki (Ed.), *Advances in Applied and Pure Mathematics* (Vol. 27, pp. 375–382). WSEAS. https://hal.science/hal-02557344.

Tanzania Police Force. (2019). *Crime Status and Road Safety Incidents Statistics – January to December 2019*. https://www.nbs.go.tz/statistics/topic/crime-statistics.

Tanzania Police Force. (2020). *Crime Status and Road Safety Incidents Statistics – January to December 2020*. https://www.nbs.go.tz/statistics/topic/crime-statistics.

Tanzania Police Force. (2023). *Crime Status and Road Safety Incidents Statistics – January to December 2023*. https://www.nbs.go.tz/statistics/topic/crime-statistics.

Tanzania Police Force. (2024). *Crime Status and Road Safety Incidents Statistics – January to December 2024*. https://www.nbs.go.tz/statistics/topic/crime-statistics.

Topolšek, D., Dragan, D., 2018. Relationships between the motorcyclists' behavioural perception and their actual behaviour. Transport 33 (1), 1. https://doi.org/10.3846/16484142.2016.1141371.

Truong, L.T., Nguyen, H.T.T., 2019. Mobile phone related crashes among motorcycle taxi drivers. Accid. Anal. Prev 132, 105288. https://doi.org/10.1016/j.aap.2019.105288.

Usami, D.S., González-Hernández, B., Persia, L., Kunsoan, N.B., Meta, E., Saporito, M.R., Schermers, G., Carnis, L., Yerpez, J., Bouhamed, N., Cardoso, J., Kluppels, L., Vandemeulebroek, F., 2021. Defining suitable safe system projects: the experience of the SaferAfrica project in five African countries. IATSS Research 45 (4), 594–601. https://doi.org/10.1016/j.iatssr.2021.08.001.

Uttra, S., Jomnonkwao, S., Watthanaklang, D., & Ratanavaraha, V. (2020). Development of self-assessment indicators for motorcycle riders in Thailand: Application of the otorcycle rider behavior questionnaire (MRBQ). *Sustainability (Switzerland)*, *12*(7 C7-2785). https://doi.org/10.3390/su12072785.

Uttra, S., Laddawan, N., Ratanavaraha, V., Jomnonkwao, S., 2020b. Explaining sex differences in motorcyclist riding behavior: an application of multi-group structural equation modeling. Int. J. Environ. Res. Public Health 17 (23), 23. https://doi.org/10.3390/ijerph17238797.

Washington, S., Karlaftis, M. G., Mannering, F., & Anastasopoulos, P. (2020). *Statistical and Econometric Methods for Transportation Data Analysis* (3rd ed.). Chapman and Hall/CRC. https://doi.org/10.1201/9780429244018.

WHO. (2023). *Global status report on road safety 2023*. https://www.who.int/publications/i/item/9789240086456.

William, N. (2022, April 21). *Bashungwa rescinds ban on Boda boda in Dar's CBD*. The Citizen. https://www.thecitizen.co.tz/tanzania/news/national/bashungwa-rescinds-ban-on-boda-boda-in-dar-s-cbd-3789622.