sustainability

MDPI

Article

Promoting Sustainable and Safe Mobility: Psychometric Validation of the MORDE Scale for Measuring Moral Disengagement in Driving Contexts

Pierluigi Cordellieri [1,*], Raffaella Nori [2], Paola Guariglia [3], Marco Giancola [4], Alessia Bonavita [5], Massimiliano Palmiero [6], Anna Maria Giannini [1] and Laura Piccardi [1,7,*]

1 Department of Psychology, Sapienza University of Rome, 00185 Rome, Italy; annamaria.giannini@uniroma1.it
2 Department of Psychology, University of Bologna, 40126 Bologna, Italy; raffaella.nori@unibo.it
3 Faculty of Social and Communication Sciences, Università Mercatorum, 00186 Rome, Italy; paola.guariglia@unimercatorum.it
4 Department of Biotechnological and Applied Clinical Sciences, University of L'Aquila, 67100 L'Aquila, Italy; marco.giancola@univaq.it
5 Faculty of Law, Giustino Fortunato University, 82100 Benevento, Italy; a.bonavita@unifortunato.eu
6 Department of Communication Sciences, University of Teramo, 64100 Teramo, Italy; mpalmiero@unite.it
7 IRCCS San Raffaele Cassino, 03043 Cassino, Italy
* Correspondence: pierluigi.cordellieri@uniroma1.it (P.C.); laura.piccardi@uniroma1.it (L.P.)

Abstract

Background: Road traffic accidents continue to be a leading cause of mortality and morbidity worldwide. Psychological and behavioural factors play a crucial role in traffic safety and are not yet fully understood. Among these, the relationship between individuals and road rules plays a key role in driving behaviour and risk perception. We introduce and validate the MORDE (Moral Disengagement in Road Driving Evaluation) scale, a novel instrument designed to assess the specific cognitive mechanisms through which drivers morally justify risky or rule-violating behaviours. **Methods:** The scale was developed and validated through a three-step process involving 1336 licensed drivers. Exploratory and confirmatory factor analyses were conducted to test its factorial structure, and internal consistency was evaluated using Cronbach's alpha. Convergent and predictive validity were assessed using self-reported measures of traffic violations and road safety attitudes. **Results:** The final 14-item version of the MORDE scale shows a robust two-factor structure: (1) Normative Justification of Transgressive Driving and (2) Attribution of Blame and Displacement of Responsibility. The instrument demonstrates strong internal reliability and significant predictive power for driving behaviours and road safety attitudes, beyond what is explained by general moral disengagement. The MORDE scale thus shows good psychometric properties and incremental validity. **Conclusions:** By identifying psychological risk factors that contribute to unsafe and unsustainable driving, the MORDE scale provides a validated tool that can support educational interventions, traffic safety campaigns, and behaviour change programs. Its use may contribute to the promotion of a safer, more responsible, and environmentally sustainable road culture.

Keywords: road safety; driving behaviour; traffic violations; moral disengagement in driving; psychological mechanisms of transgression; psychometric validation

check for updates

Academic Editor: Isidoro Russo

Received: 31 July 2025
Revised: 6 September 2025
Accepted: 8 September 2025
Published: 10 September 2025

Citation: Cordellieri, P.; Nori, R.; Guariglia, P.; Giancola, M.; Bonavita, A.; Palmiero, M.; Giannini, A.M.; Piccardi, L. Promoting Sustainable and Safe Mobility: Psychometric Validation of the MORDE Scale for Measuring Moral Disengagement in Driving Contexts. *Sustainability* **2025**, *17*, 8151. https://doi.org/10.3390/su17188151

1. Introduction

Road traffic accidents represent one of the most significant public health challenges of our time. According to the most recent data from the World Health Organization [1], approximately 1.19 million individuals lose their lives in road traffic accidents annually across the globe, with an additional 20 to 50 million people sustaining non-fatal injuries [1]. These statistics underscore that road traffic collisions have become the leading cause of death for children and young adults aged 5–29 years on a global scale, which represents a significant loss of productive life years and imposes substantial economic and social burdens on societies worldwide.

In the European context, significant variations exist in road safety performance among member states. Italy holds an intermediate position, ranking 11th among 27 European countries in terms of the lowest fatalities per million inhabitants, with 40 road fatalities per million residents, slightly below the European average of 42. Despite this relatively advantageous ranking, the absolute figures remain concerning, as 2395 individuals lost their lives in traffic accidents in Italy in 2020 alone. The trajectory of Italy's mortality rate has closely mirrored the broader European Union trend since 2001, with notable reductions observed during the COVID-19 pandemic period of 2020–2021 due to mobility restrictions [2,3].

1.1. The Multifaceted Nature of Road Traffic Accidents

Road traffic accidents represent a critical public health challenge, arising from a complex interplay of human, environmental, and vehicle-related factors. Human errors, such as distractions, fatigue, substance use, and risky behaviors, are significant contributors to traffic accidents. Research consistently demonstrates that different age groups exhibit distinct risk profiles: young drivers are particularly susceptible to speeding, alcohol consumption, and loss of vehicle control. Conversely, older drivers are more prone to perceptual or judgment errors, particularly at intersections [4,5]. Fatigue and drowsiness represent insidious risk factors, often underrecognized by drivers themselves, yet they significantly impair response times and decision-making capabilities, especially during nighttime driving or following extended periods behind the wheel [6]. Substance use remains a substantial threat, with alcohol identified as the most significant risk factor, increasing the likelihood of fatal accidents nearly eighteenfold. Cannabis and other psychoactive substances also elevate crash risk, particularly when consumed in conjunction with alcohol [7–9]. Moreover, environmental factors, including road infrastructure quality, lighting conditions, and meteorological variables, further influence accident rates and severity [10,11]. Emerging technological solutions, such as artificial intelligence-based driver attention monitoring systems and predictive analytics, offer promising avenues for detecting unsafe driving patterns and preventing accidents before they transpire [12]. The substantial societal costs associated with traffic accidents, particularly in high-density populated urban areas, provide a compelling economic rationale for comprehensive policy interventions, including corrective taxation and infrastructure enhancements [13].

Understanding the psychological mechanisms that allow drivers to morally justify risky or transgressive behaviors is not only crucial for improving road safety but also for advancing the goals of sustainable mobility. Individual attitudes and behavioral patterns significantly influence traffic dynamics, energy consumption, and environmental impact—particularly in urban environments, where unsafe driving practices can deter the adoption of alternative and low-impact transport modes. By addressing these psychological dimensions, this study contributes to the development of more integrated strategies aimed at fostering both safety and sustainability within modern mobility systems.

1.2. Theoretical Frameworks for Understanding Driver Behavior

Effectively predicting accidents requires a comprehensive understanding of the psychological mechanisms that underpin drivers' behavior and decision-making processes. The Theory of Planned Behaviour (TPB: [14]) provides a robust framework for understanding how attitudes, subjective norms, and perceived behavioral control collectively influence drivers' intentions and actual behaviors. Extensive research has shown that these three components consistently account for substantial variance in various driving behaviors, including speeding, distracted driving, driving under the influence, and seat belt usage, with attitudes frequently serving as the strongest predictor of behavioral intention [15–18]. The TPB's effectiveness lies in its inclusion of both volitional and non-volitional behaviours while integrating social and personal factors [19]. It operates under the assumption that individuals engage in specific behaviours when they perceive the expected outcomes to be beneficial to themselves. However, this self-interested decision-making process can conflict with moral behavior, which aligns with generally accepted societal norms of conduct [20].

Within the context of driving, moral considerations have been extensively examined in traffic safety research, with TPB-based studies investigating a variety of behaviours including aggressive manoeuvres, speeding, mobile phone usage while driving, and drink-driving [21–28]. Research has demonstrated substantial interactions among moral values, moral reasoning, and emotional responses. Notably, studies show that individuals with diminished moral values exhibit increased tolerance toward aggressive driving behaviors [29]. Similarly, Du and Chang [30] found that ethical beliefs substantially influence perceptions of responsibility for other drivers, subsequent anger responses, and the escalation of aggressive driving behavior. Furthermore, Veldscholten [31] found that norm-adherent driving behavior is fundamentally motivated by concerns for the overall safety of the traffic system, rather than by self-serving motives such as the avoidance of punishment. This body of research revealed that lower levels of moral reasoning correlate with a higher incidence of accidents, increased driving speeds, and greater spatial aggression while driving.

1.3. Moral Disengagement Theory and Its Applications

Bandura's [32] seminal work on moral disengagement theory identified eight distinct psychological mechanisms that permit individuals to bypass their moral standards and justify harmful behavior without experiencing guilt or self-condemnation. These mechanisms consist of the following: (1) *Moral Justification*, which involves reframing harmful actions as serving worthwhile purposes; (2) *Euphemistic Labeling*, which utilizes sanitized language to diminish perceived severity; (3) *Advantageous Comparison*, where one compares actions to more severe behaviors to minimize their significance; (4) *Displacement of Responsibility*, which attributes actions to authority figures or external pressures; (5) *Diffusion of Responsibility*, which spreads accountability across groups; (6) *Distortion or Disregard of Consequences*, which minimizes or ignores resultant harm; (7) *Dehumanization*, which involves viewing victims as less deserving of moral consideration; and (8) *Attribution of Blame*, which entails holding victims responsible for their suffering [33,34].

These mechanisms operate by temporarily disabling the self-regulatory processes that would typically generate guilt or self-censure following wrongdoing, enabling individuals to preserve positive self-images while engaging in unethical behavior. Research has shown that moral justification and vilification are particularly influential in facilitating harmful conduct [33]. The universality of these mechanisms has been evidenced across various contexts, including workplace misconduct, bullying, sports, corporate malfeasance, and violent extremism [35–38].

Moral disengagement within driving contexts pertains to the psychological processes through which drivers justify or rationalize aggressive, risky, or non-compliant behaviors that would ordinarily conflict with their moral standards. Empirical research indicates that drivers exhibiting higher levels of moral disengagement are significantly more likely to engage in aggressive driving behaviors, including retaliation against other drivers and deliberate violations of traffic rules, often through harm minimization or blame attribution to others [39].

Importantly, this tendency is not confined to individuals who identify themselves as inherently aggressive; even those drivers who perceive themselves as generally moral may disengage their typical self-regulatory mechanisms within the driving context [40]. Recent research has established connections between moral disengagement and reduced compliance with traffic regulations; however, strong self-control can mitigate these effects, thereby suggesting that interventions aimed at enhancing self-control may improve road safety outcomes [41].

The advent of autonomous vehicles has introduced new facets to moral disengagement research, with studies indicating that moral disengagement can heighten aggression towards these vehicles, influenced by individual personality traits, driving styles, and attitudes toward road sharing [39,42]. Moreover, anger rumination has been identified as a mediating factor in the relationship between moral disengagement and road rage, further elevating the risk of hazardous driving behaviors [43,44].

These collective findings underscore the critical need to address moral disengagement within driver education programs and interventions to promote safer driving habits and reduce traffic accident rates (see also [45]).

1.4. Instruments to Measure Moral Disengagement in the Driving Context

Taking into account the importance of traffic accidents and individual responsibilities, several instruments have been developed in recent years to measure moral disengagement within driving contexts. Notably, some studies have employed adapted versions of Bandura's scale to evaluate how drivers rationalize aggression or non-compliance with traffic regulations [39,40,46]. Nevertheless, these instruments exhibit several limitations. Juniarli and Effendi [46] presented their findings in Indonesia, with only the abstract available in English, restricting the accessibility of their scale and making their findings culturally specific. On the other hand, Paschalidis and Chen [39] explored the topic of autonomous vehicles, resulting in a highly focused scale on this specific issue. Furthermore, instruments tailored to specific driving contexts (such as interactions with autonomous vehicles) may lack validation across different cultures, road environments, or types of drivers, thus constraining their generalizability. These criticisms highlight the need for further refinement and validation of moral disengagement measures that are attuned to the complexities of driving behavior.

In addition, recent methodological advances such as metaheuristic optimization algorithms—for instance, the Polar Fox Optimization [47]—have been proposed to improve parameter estimation and model fitting in complex data contexts. While their application to psychometric scale validation remains at an exploratory stage, they represent a promising avenue for future research in measurement development.

1.5. Study Objectives and the MORDE Scale

In light of the substantial public health impact of road traffic accidents and the growing acknowledgement of moral disengagement as a significant contributor to risky driving behaviors, there exists an urgent need for validated psychometric instruments able to assess moral disengagement specifically within driving contexts. The present study endeavours to adapt and apply Bandura's [32] theoretical framework of moral disengagement mechanisms to driving behaviour, with particular focus on the cognitive processes that justify traffic violations and diminish responsibility towards other road users.

To address this need, we have developed the MORDE (Moral Disengagement in Road Driving Evaluation) scale, a comprehensive psychometric instrument specifically designed to assess the implementation of moral disengagement mechanisms within the driving context. This study seeks to investigate both external and internal validity of the MORDE scale, thereby providing the research community and practitioners with a robust tool for understanding and measuring the psychological processes that contribute to hazardous driving behaviors.

2. Materials and Methods

2.1. Participants

The study involved three groups of participants recruited in successive phases. All participants across the three groups reported holding a valid driver's license and regularly operating a motor vehicle. The first group was used to explore the factorial structure of the MORDE scale through an Exploratory Factor Analysis (EFA): 333 licensed drivers (140 males, 193 females), with a mean age of 29.0 years (*SD* = 14.2). The second separate group served to confirm the factorial model via Confirmatory Factor Analysis (CFA): 304 individuals (146 males, 158 females), with a mean age of 32.0 years (*SD* = 15.0). The third, larger sample was used for the assessment of the scale's external validity: 699 participants (304 males, 395 females), with a mean age of 30.8 years (*SD* = 15.1). Specifically, concurrent validity was tested through correlations with a general moral disengagement scale, while predictive validity was evaluated by examining the extent to which the MORDE factors predicted self-reported driving behaviors and attitudes toward road safety.

2.2. Procedure

Participants were recruited via online platforms and university mailing lists and were informed of the study's objectives and the anonymous, voluntary nature of their participation. After providing informed consent, participants completed a self-report questionnaire administered through a secure web-based platform. Data collection procedures adhered to the ethical standards outlined in the Declaration of Helsinki and were approved by the Ethics Review Board of the Department of Psychology, La Sapienza University of Rome (IRB 2414/2019).

2.3. Measures

The study employed a set of standardized and context-specific instruments designed to assess moral disengagement, driving-related behaviors, and attitudes.

2.3.1. Moral Disengagement

General Moral Disengagement

Moral disengagement was assessed using the 32-item scale developed by Caprara et al. [48], based on Bandura's [32] eight mechanisms. Although items reflect distinct disengagement strategies, the scale is commonly employed as a unidimensional measure of general moral disengagement. Participants responded using a 5-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). The scale has demonstrated high internal consistency (α = 0.90) across various populations.

Instrument Development

Moral Disengagement in Road Driving Evaluation (MORDE)

The MORDE scale (Moral Disengagement in Road Driving Evaluation) was developed to assess the use of moral disengagement mechanisms in driving contexts, based on Bandura's [32] framework. From an initial pool of 32 items, 24 were retained by two independent psychologists for their theoretical representativeness and semantic clarity. This step was therefore conceptually driven and served as an expert content review, aimed at maximizing the content validity of the scale prior to empirical testing. No statistical reduction was applied at this stage, as the focus was on theoretical representativeness rather than psychometric performance. Subsequent psychometric refinement, based on exploratory and confirmatory factor analyses, reduced the pool to 14 items. Items were rated on a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), with higher scores indicating greater endorsement of morally disengaged justifications for risky or norm-violating driving behaviors.

2.3.2. Driving Attitudes and Behaviours

Driving Attitudes Scale (DAS)

Attitudes toward road safety were measured using the original 16-item Driving Attitudes Scale (DAS) developed by Iversen and Rundmo [49]. The scale assesses three core domains: (1) attitudes toward rule violations and speeding, (2) attitudes toward the careless driving of others, and (3) attitudes toward drinking and driving. Participants responded to each item on a five-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). Higher scores indicate greater endorsement of safe and responsible attitudes toward road use.

Manchester Driver Behaviour Questionnaire (DBQ)

Aberrant driving behaviour was assessed using the Italian adaptation of the Manchester Driver Behaviour Questionnaire (DBQ), originally developed by Reason et al. [50] and validated in Italy by Smorti and Guarnieri [51]. The 27-item version used in this study asks participants to rate the frequency of various behaviours on a 6-point Likert scale (1 = "Never" to 6 = "Nearly all the time").

The DBQ includes four subscales: aggressive violations, ordinary violations, errors, and lapses, which are grouped into two higher-order dimensions: violations (both aggressive and ordinary) and unintentional errors (errors and lapses). This hierarchical structure enables a differentiated assessment of deliberate versus unintentional risky driving behaviours.

Cronbach's alpha coefficients were computed for each subscale and for the second-order factors: aggressive violations ($\alpha = 0.74$), ordinary violations ($\alpha = 0.80$), errors ($\alpha = 0.78$), lapses ($\alpha = 0.76$).

3. Results

3.1. Data Analysis

Data analysis was conducted in three sequential stages, each corresponding to a specific research objective: (a) exploring the factorial structure of the MORDE scale, (b) confirming the derived structure through independent sample validation, and (c) assessing external validity through convergent and predictive criteria.

3.2. Exploratory and Confirmatory Factor Analyses

3.2.1. Exploratory Factor Analysis

An initial Exploratory Factor Analysis (EFA) was conducted on the 24-item version of the MORDE scale using the Minimum Residual (MinRes) extraction method with oblimin rotation, appropriate for correlated latent constructs and robust against violations of multivariate normality. Sampling adequacy was excellent, as indicated by the Kaiser–Meyer–Olkin measure (KMO = 0.915), which exceeds the conventional threshold of 0.60 for acceptable adequacy and 0.80 for meritorious adequacy [52], and Bartlett's [53] test confirmed the data's suitability for factor analysis ($\chi^2(276) = 2966$, $p < 0.001$). Factor retention was based on multiple criteria, including eigenvalues >1, scree plot, and theoretical interpretability. In addition, Parallel Analysis [54] and the Minimum Average Partial test [55] were conducted, both supporting the retention of two factors. Together, these criteria indicated a two-factor solution (eigenvalues = 9.68 and 1.80), explaining 35.3% of the total variance (20.8% and 14.5%, respectively). Model fit indices for this 24-item solution were acceptable but not optimal, with an RMSEA of 0.0656 (90% *CI* [0.0609, 0.0706]) and a Tucker–Lewis Index (TLI) of 0.807. According to conventional benchmarks, RMSEA values <0.08 indicate acceptable fit and <0.05 good fit [56,57], while TLI $\geq$ 0.90 indicates adequate fit and $\geq$0.95 good fit [57,58]. The chi-square test was significant ($\chi^2(463) = 1127$, $p < 0.001$), as expected with large sample sizes, but the absolute and incremental fit indices suggested room for improvement. Nine items (1, 4, 7, 8, 9, 14, 16, 18, 24) exhibited psychometric weaknesses, with some showing primary loadings below 0.40 (e.g., 4, 9, and 14), others demonstrating high uniqueness (e.g., 1), and still others displaying cross-loadings or conceptual ambiguity (e.g., 16, 24). Following recommended guidelines for scale refinement [59,60], these items were excluded to enhance factorial clarity and improve model fit.

In addition, although Item 23 demonstrated an acceptable loading on the second factor, its focus on systemic and infrastructural causes of traffic violations was conceptually misaligned with the other items, which primarily addressed interpersonal blame attribution and externalized responsibility. Following best practices for construct validity and scale refinement [61,62], we excluded this item, prioritizing theoretical coherence over minor statistical advantages.

A revised EFA on the resulting 14-item version of the MORDE scale replicated the two-factor structure, now explaining 42.3% of the total variance (22.0% for Factor 1, 20.3% for Factor 2), with improved model fit indices: RMSEA = 0.0599 (90% *CI* [0.0466, 0.0735]) and TLI = 0.926. Both indices fall within the acceptable-to-good range (RMSEA < 0.08, TLI $\geq$ 0.90). Sampling adequacy was meritorious (KMO = 0.88), and Bartlett's test confirmed the suitability of the data for factor analysis ($\chi^2(91) = 1568$, $p < 0.001$).

To provide a more rigorous justification for the factor retention criteria and address the reviewer's request, we conducted a Parallel Analysis and applied the Minimum Average Partial (MAP) criterion. The results of the Parallel Analysis were unequivocal, suggesting that the optimal number of factors to retain was two. The MAP criterion further confirmed this conclusion.

Factor loadings and uniqueness estimates for all items are reported in Table 1, while the scree plot supporting the two-factor solution is displayed in Figure 1.

To further evaluate the factorial structure, we also compared alternative solutions. The one-factor model explained only 30.1% of the variance and showed very poor fit indices ($\chi^2(77) = 547$, TLI = 0.623, RMSEA = 0.135, 90% *CI* [0.125–0.146], BIC = 99.8), indicating that a unidimensional structure does not adequately capture the construct. The three-factor solution explained 45.4% of the variance and presented somewhat better fit indices ($\chi^2(52) = 98.8$, TLI = 0.944, RMSEA = 0.052, 90% *CI* [0.036–0.068], BIC = −203). However, the additional factor did not yield a coherent theoretical interpretation, as it grouped together items without conceptual consistency, despite moderate inter-factor correlations. By contrast, the two-factor solution was strongly supported by both the scree plot and theoretical considerations and was therefore retained for subsequent validation in the CFA.

Table 1. Factor loadings and uniqueness estimates for the final 14 items of the MORDE scale (N = 333).

N.	Item Content	Factor 1 *Normative Justification*	Factor 2 *Blame Externalization*	Uniqueness
1	Red light due to horn pressure	0.53	—	0.70
2	Minimizing seriousness of rule violations	0.78	—	0.39
3	Cyclists responsible for their own safety	—	0.63	0.62
4	Drivers' lack of intelligence	—	0.71	0.53
5	Everyone breaks the rules	0.78	—	0.40
6	Running red lights on empty roads	0.74	—	0.51
7	Minimizing disabled parking violations	0.46	—	0.75
8	Reckless motorcyclists	—	0.58	0.58
9	Shared blame for drunk driving accidents	—	0.41	0.84
10	Cyclists as traffic obstacles	—	0.74	0.49
11	Speeding justified by vehicle capabilities	0.57	—	0.59
12	Blaming friends for driving accidents	—	0.63	0.55
13	Poor infrastructure as cause of violations	0.64	—	0.55
14	Blaming pedestrians for accidents	—	0.63	0.58

Note. Extraction method: Minimum Residual; Rotation method: Oblimin. Higher loadings (>0.30) are typically considered substantial.

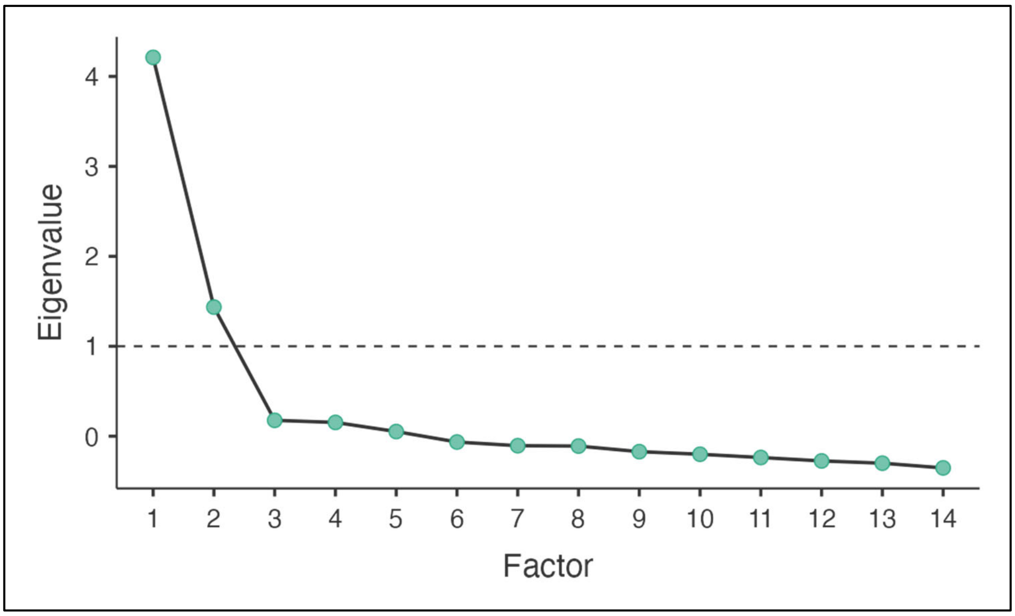

Figure 1. Scree plot of eigenvalues for the 14-item MORDE scale. The plot clearly shows a two-factor solution, with only the first two factors exceeding the eigenvalue threshold of 1 (dashed line).

For the two-factor solution, model fit was excellent, with a chi-square statistic of $\chi^2(64) = 141$, $p < 0.001$. The inter-factor correlation remained moderate (r = 0.414), supporting the use of oblique rotation. The final factor structure was theoretically interpretable as follows:

Factor 1: Normative Justification of Transgressive Driving (Normative Justification), representing cognitive mechanisms that normalize or morally justify risky driving behavior.
Factor 2: Attribution of Blame and Displacement of Responsibility (Blame Externalization), reflecting tendencies to externalize blame or responsibility onto other road users.

Although some items exhibited relatively high uniqueness values—suggesting part of their variance was not fully accounted for by the extracted factors—all retained items showed primary loadings above acceptable thresholds and clear theoretical relevance to the construct under investigation. In line with the established guidelines [59,63], we considered items problematic only when uniqueness exceeded 0.85. The highest observed value was 0.84, which falls just below this threshold, and thus the item was retained. A notable exception was item 1, which had a CFA loading of 0.29, slightly below the conventional threshold. However, this item was retained for its robust conceptual relevance and its significant contribution to the overall scale, as evidenced by its high item-total correlation. Additionally, all retained items consistently showed corrected item–total correlations above 0.30 and acceptable inter-item correlations, supporting their statistical adequacy. The complete correlation matrices are not reported for reasons of space but are available from the authors upon request. The decision to retain these items aligns with established psychometric guidelines [59,60], emphasizing both factorial interpretability and theoretical coherence.

After testing multiple alternative models, the 14-item version of the MORDE scale offered the best balance between parsimony, conceptual clarity, and statistical adequacy. This version yielded satisfactory fit indices (e.g., RMSEA, TLI) and avoided the retention of items characterized by either conceptual inconsistency or psychometric weakness. Consequently, the 14-item two-factor structure was adopted for all subsequent analyses

3.2.2. Confirmatory Factor Analysis

To validate the factorial structure emerging from the exploratory analysis, a confirmatory factor analysis (CFA) was performed on an independent sample (N = 304), testing the hypothesized two-factor model derived from the 14-item version of the MORDE scale.

Alternative Models

For comparison, we also tested a unidimensional model in which all items loaded onto a single latent factor. This model showed very poor fit indices, $\chi^2(77) = 520$, $p < 0.001$, CFI = 0.607, TLI = 0.536, SRMR = 0.117, RMSEA = 0.137 (90% *CI* [0.126–0.149]), with substantially higher AIC (10,593) and BIC (10,749), indicating that a one-factor solution does not adequately represent the construct. A three-factor model was also examined, $\chi^2(74) = 167$, $p < 0.001$, CFI = 0.917, TLI = 0.898, SRMR = 0.0495, RMSEA = 0.0644 (90% *CI* [0.051–0.077]), AIC = 10,247, BIC = 10,414. Although its fit indices were comparable to those of the two-factor solution, the third factor did not yield a coherent theoretical interpretation and was highly correlated with the other latent dimensions. Table 2 summarizes the comparative fit indices for the one-, two-, and three-factor models. As shown, the two-factor solution provided the most adequate and theoretically coherent representation of the data.

Table 2. Comparative fit indices for one-, two-, and three-factor confirmatory models of the MORDE scale (N = 304).

Model	χ^2 (df)	CFI	TLI	SRMR	RMSEA [90% CI]	AIC	BIC
One-factor	520 (77)	0.607	0.536	0.117	0.137 [0.126–0.149]	10,593	10,749
Two-factor	171 (76)	0.915	0.899	0.0517	0.064 [0.0515–0.0771]	10,246	10,406
Three-factor	167 (74)	0.917	0.898	0.0495	0.0644 [0.0515–0.0774]	10,247	10,414

Note. CFI = Comparative Fit Index; TLI = Tucker–Lewis Index; SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error of Approximation; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

Factor Loadings and Inter-Factor Covariance

The two latent factors showed a significant covariance of 0.346 (SE = 0.0637), with a z-value of 5.42 ($p < 0.001$), supporting the theoretical assumption of a moderate association between the two dimensions of moral disengagement in driving contexts. Although Item 1 presented a relatively low standardized loading in the CFA (0.29), its reliability statistics within the corresponding factor were satisfactory (item–rest correlation = 0.393). Furthermore, its removal would slightly decrease internal consistency (Cronbach's α from 0.778 to 0.773; McDonald's ω from 0.782 to 0.779). Given the negligible impact on reliability and the theoretical importance of the item content, it was retained. Internal consistency indices confirmed the reliability of the scale as a whole. For Factor 1, Cronbach's α was 0.778 and McDonald's ω was 0.782; for Factor 2, Cronbach's α was 0.790 and McDonald's ω was 0.800. For the overall 14-item scale, Cronbach's α was 0.802 and McDonald's ω was 0.782, indicating good reliability at both the factor and total levels.

Model Fit Indices

Confirmatory factor analyses were conducted using the robust maximum likelihood (MLR) estimator with Pearson correlations, as implemented in Jamovi (lavaan). While WLSMV is often preferred for strictly ordinal data, MLR is considered appropriate for Likert-type scales with five or more response categories. Model fit was assessed using multiple indices (SRMR, RMSEA, CFI, and TLI), whose formulas are reported below for transparency

Although the chi-square test of exact fit was significant, $\chi^2(76) = 171$, $p < 0.001$—as expected given the sensitivity of the test to large sample sizes—complementary indices were examined to assess model fit. The SRMR was 0.0517, well below the recommended cutoff of 0.08 for acceptable fit [56], indicating a satisfactory level of residual discrepancy.

The RMSEA was 0.0642, with a 90% confidence interval ranging from 0.0515 to 0.0771, which falls within the conventionally acceptable range (<0.08; [53,54]). Incremental fit indices were CFI = 0.915 and TLI = 0.899. While the TLI was marginally below the conventional 0.90 cutoff, model evaluation was based on the joint consideration of multiple indices (*SRMR*, *RMSEA* with *CI*, and CFI), all of which consistently suggested an adequate overall fit for the hypothesized two-factor solution [57,58]. In terms of model parsimony, the AIC = 10,246 and BIC = 10,406 values suggest a favorable trade-off between model complexity and data representation.

For transparency, the formulas used to compute these indices are reported below. RMSEA is calculated as follows:

$$\mathrm{RMSEA} = \sqrt{max\left(\frac{\chi^2 - df}{df \times (N-1)}, 0\right)}$$

The Tucker–Lewis Index (TLI) is defined as follows:

$$\mathrm{TLI} = \frac{\left(\frac{\chi^2_{null}}{df_{null}}\right) - \left(\frac{\chi^2_{model}}{df_{model}}\right)}{\left(\frac{\chi^2_{null}}{df_{null}}\right) - 1}$$

In line with common practice, we report the 90% confidence interval for RMSEA (0.0515–0.0771). Confidence intervals are not typically reported for the TLI, so only the point estimate is provided.

The factorial structure is illustrated in Figure 2, while the corresponding standardized loadings are reported in Table 3 (all $p < 0.001$).

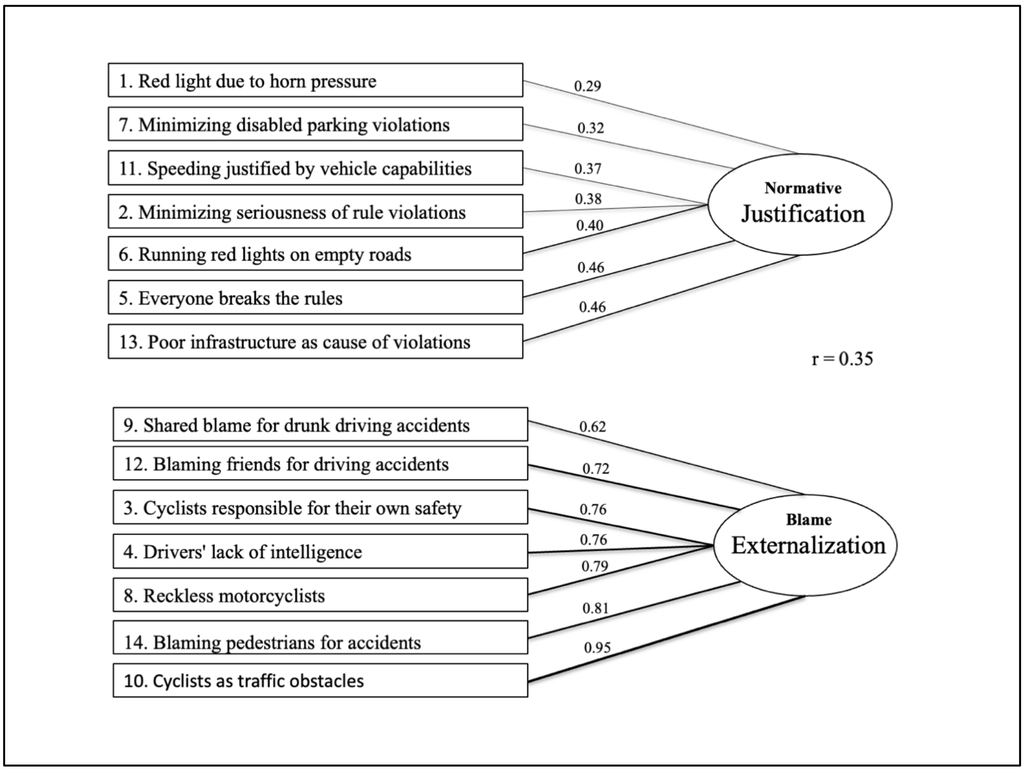

Figure 2. Path diagram of the Confirmatory Factor Analysis (CFA) for the MORDE scale. The model specifies two correlated latent factors, "Normative Justification" and "Blame Externalization". Standardized factor loadings are shown on the arrows, with line thickness proportional to their magnitude. The correlation between the two latent factors was r = 0.35. Note. All standardized loadings are statistically significant at $p < 0.001$. Factor correlation between "Normative Justification" and "Blame Externalization": r = 0.35.

Table 3. Standardized factor loadings from the confirmatory factor analysis (CFA) of the 14-item MORDE scale. All loadings are statistically significant at $p < 0.001$. The two latent factors are Normative Justification and Blame Externalization.

Item	Content	Factor	Estimate	SE	Z
1	Red light due to horn pressure	Normative Justification	0.29	0.04	7.40 ($p < 0.001$)
2	Minimizing seriousness of rule violations	Normative Justification	0.38	0.03	11.21 ($p < 0.001$)
3	Cyclists responsible for their own safety	Blame Externalization	0.76	0.08	9.58 ($p < 0.001$)
4	Drivers' lack of intelligence	Blame Externalization	0.76	0.07	10.52 ($p < 0.001$)
5	Everyone breaks the rules	Normative Justification	0.46	0.03	13.47 ($p < 0.001$)
6	Running red lights on empty roads	Normative Justification	0.4	0.04	10.86 ($p < 0.001$)
7	Minimizing disabled parking violations	Normative Justification	0.32	0.04	8.90 ($p < 0.001$)
8	Reckless motorcyclists	Blame Externalization	0.79	0.07	11.90 ($p < 0.001$)
9	Shared blame for drunk driving accidents	Blame Externalization	0.62	0.08	7.44 ($p < 0.001$)
10	Cyclists as traffic obstacles	Blame Externalization	0.95	0.07	13.76 ($p < 0.001$)
11	Speeding justified by vehicle capabilities	Normative Justification	0.37	0.05	7.88 ($p < 0.001$)

Table 3. *Cont.*

Item	Content	Factor	Estimate	SE	Z
12	Blaming friends for driving accidents	Blame Externalization	0.72	0.06	11.41 ($p < 0.001$)
13	Poor infrastructure as cause of violations	Normative Justification	0.46	0.04	11.59 ($p < 0.001$)
14	Blaming pedestrians for accidents	Blame Externalization	0.81	0.06	12.55 ($p < 0.001$)

Standardized factor loadings from the Confirmatory Factor Analysis (CFA) of the 14-item MORDE scale.

Overall Interpretation

These results provide strong empirical support for the adequacy of the two-factor model. Absolute fit indices indicate a good correspondence between the model and the data, and the moderate correlation between factors confirms the theoretical rationale for using an oblique rotation in the EFA. While minor refinements may be possible, the CFA confirms the structural validity and theoretical soundness of the 14-item MORDE scale, supporting its use in both research and applied settings in traffic psychology.

3.3. Validity Analyses

3.3.1. Convergent Validity

To assess the convergent validity of the MORDE scale, we examined its correlation with the General Moral Disengagement Scale [48], which measures a domain-general tendency to morally disengage across various life contexts. Pearson's correlation coefficients were calculated between the two MORDE factors—Normative Justification of Transgressive Driving (NJT) and Attribution of Blame and Displacement of Responsibility (ABD)—and total scores on the General Moral Disengagement scale.

Results indicated that both MORDE factors were positively and significantly correlated with General Moral Disengagement. Specifically, the NJT factor showed a strong correlation ($r = 0.64$, $p < 0.001$), suggesting that individuals with a higher general tendency to morally disengage are also more likely to justify transgressive driving behaviors. The ABD factor also demonstrated a moderate positive correlation ($r = 0.51$, $p < 0.001$), indicating that externalization of blame and responsibility in driving contexts is meaningfully associated with general moral disengagement. The two MORDE factors were moderately interrelated ($r = 0.36$, $p < 0.001$), consistent with the theoretical assumption of related but distinct dimensions.

3.3.2. Predictive and Incremental Validity

To evaluate the predictive and incremental validity of the MORDE scale, hierarchical multiple regression analyses were conducted on a third sample (N = 699), testing whether the two MORDE factors predicted driving-related attitudes and behaviors above and beyond the variance explained by General Moral Disengagement.

For each outcome variable, three models were tested:

Model 1: Included the General Moral Disengagement Scale (GMD) as the sole predictor.
Model 2: Added the NJT factor.
Model 3: Added the ABD factor, thus including both MORDE factors alongside GMD.

This approach allowed us to assess not only the unique contribution of each MORDE factor (Predictive validity) but also the Incremental variance explained (ΔR^2) beyond the effects of general moral disengagement.

3.3.3. Driving Attitudes Scale (DAS)

Positive Attitudes Toward Road Safety (DAS—Positive Dimension)

For positive attitudes toward traffic safety, NJT significantly improved the model over GMD alone ($\Delta R^2 = 0.0258$, $F(1, 692) = 18.9$, $p < 0.001$; $f^2 = 0.030$, small), and ABD provided a further significant increment ($\Delta R^2 = 0.0862$, $F(1, 691) = 69.4$, $p < 0.001$; $f^2 = 0.100$, small-to-medium), yielding a final R^2 of 0.141. In the final model, both NJT ($\beta = -0.57$, $p < 0.001$) and ABD ($\beta = 0.51$, $p < 0.001$) were significant, along with GMD ($\beta = -0.53$, $p < 0.001$). Negative coefficients indicate that higher disengagement is associated with lower endorsement of positive safety attitudes.

Negative Attitudes Toward Road Safety (DAS—Negative Dimension)

For negative attitudes toward safety rules and law enforcement, both NJT ($\Delta R^2 = 0.0496$, $F(1, 692) = 52.6$, $p < 0.001$; $f^2 = 0.078$, small-to-medium) and ABD ($\Delta R^2 = 0.0175$, $F(1, 691) = 19.0$, $p < 0.001$; $f^2 = 0.028$, small) significantly improved the model, bringing the final R^2 to 0.365. In the final step, all three predictors—GMD ($\beta = 0.55$, $p < 0.001$), NJT ($\beta = 0.50$, $p < 0.001$), and ABD ($\beta = 0.16$, $p < 0.001$)—emerged as significant and positive predictors.

Driving Violations (DBQ—Violations Subscale)

For self-reported driving violations, the inclusion of NJT in Model 2 led to a significant increase in explained variance ($\Delta R^2 = 0.0098$, $F(1, 696) = 8.13$, $p = 0.004$). Adding ABD in Model 3 further improved the model fit ($\Delta R^2 = 0.0246$, $F(1, 695) = 20.89$, $p < 0.001$), resulting in a final R^2 of 0.182. Both NJT ($\beta = 0.17$, $p = 0.008$) and ABD ($\beta = 0.16$, $p < 0.001$) showed significant positive associations with driving violations, after controlling for GMD ($\beta = 0.33$, $p < 0.001$).

Errors (DBQ—Errors Subscale)

For self-reported driving errors, NJT again contributed significantly ($\Delta R^2 = 0.0190$, $F(1, 696) = 15.78$, $p < 0.001$; $f^2 = 0.023$, small). ABD added a smaller but significant increment ($\Delta R^2 = 0.0058$, $F(1, 695) = 4.87$, $p = 0.027$; $f^2 = 0.007$, negligible-to-small). The final model explained 16.9% of the variance ($R^2 = 0.169$), with both NJT ($\beta = 0.18$, $p < 0.001$) and ABD ($\beta = 0.06$, $p = 0.028$) emerging as significant predictors, alongside GMD ($\beta = 0.25$, $p < 0.001$).

Lapses (DBQ—Lapses Subscale)

For lapses, NJT significantly improved the model ($\Delta R^2 = 0.0081$, $F(1, 696) = 6.13$, $p = 0.014$; $f^2 = 0.009$, negligible-to-small), and ABD again accounted for additional variance ($\Delta R^2 = 0.0271$, $F(1, 695) = 21.04$, $p < 0.001$; $f^2 = 0.030$, small), resulting in a total R^2 of 0.104. Both NJT ($\beta = 0.13$, $p = 0.024$) and ABD ($\beta = 0.14$, $p < 0.001$) were significant predictors, whereas GMD did not reach statistical significance ($\beta = 0.13$, $p = 0.059$).

Aggressive Violations (DBQ—Aggressive Violations Subscale)

Regarding aggressive driving violations, the addition of NJT did not produce a statistically significant increment ($\Delta R^2 = 0.0032$, $F(1, 696) = 2.39$, $p = 0.122$). However, ABD contributed a meaningful increase ($\Delta R^2 = 0.0285$, $F(1, 695) = 22.07$, $p < 0.001$; $f^2 = 0.032$, small). In the final model ($R^2 = 0.102$), ABD ($\beta = 0.24$, $p < 0.001$) and GMD ($\beta = 0.28$, $p = 0.015$) were significant predictors, while NJT was not ($\beta = 0.13$, $p = 0.190$).

3.3.4. Summary of Predictive and Incremental Validity

Across all models, the inclusion of MORDE factors significantly increased the explained variance in both driving behaviors and attitudes toward traffic safety, even after controlling for general moral disengagement. Cohen's f^2 effect sizes ranged between 0.007 and 0.100, corresponding to small-to-medium effects according to Cohen's [60,64] benchmarks. Although modest in size, these effects were statistically reliable: given the large sample in the predictive validity analyses (N = 699), post hoc power analysis indicated that even small effects ($f^2 = 0.02$) could be detected with power greater than 0.95.

These findings confirm that NJT and ABD provide consistent, domain-specific contributions beyond GMD. Importantly, even small incremental effects are practically meaningful in applied contexts such as road safety, where identifying specific moral disengagement mechanisms can guide targeted interventions and preventive strategies

4. Discussion

The present study aimed to develop and validate a psychometric instrument to measure moral disengagement in the context of driving—the MORDE scale—and to examine its factorial structure, internal consistency, as well as its convergent and predictive validity. The results confirm the instrument's robustness and, most importantly, highlight a theoretically and practically relevant element: the identification of a two-factor structure that distinguishes between functionally and psychologically distinct dimensions of moral disengagement in driving.

Unlike most existing scales on moral disengagement, which typically adopt a single-factor structure [33,48,65], both exploratory and confirmatory factor analyses revealed two distinct and interpretable factors. The first concerns the use of justifications for violating traffic laws and regulations, while the second reflects mechanisms of displacement of responsibility and dehumanization toward other road users. This distinction suggests that moral disengagement in driving is not a unitary construct but can be conceptualized as encompassing at least two domains: a normative domain, relating to one's relationship with social and legal rules, and a relational domain, involving moral perception and evaluation of other drivers.

This articulation represents a significant theoretical advancement over previous models. The Driving Moral Disengagement Scale (DMDS) by Swann et al. [65], for example, proposes a unidimensional solution that, although useful, does not capture the different ways in which moral disengagement can manifest in road behavior. By contrast, the MORDE scale allows for the distinction between individuals who tend to minimize the seriousness of rule violations and those who justify their actions by attributing blame to others or by perceiving other drivers as less morally worthy or even responsible for adverse outcomes.

4.1. Implication for Road Safety: From Individual Assessment to Systematic Prevention

The MORDE scale has direct implications for road safety interventions that extend beyond traditional approaches. The distinction between Normative Justification and Blame Externalization suggests that safety interventions should be tailored to address different psychological profiles among drivers.

For individuals scoring high on Normative Justification, safety programs could focus on reinforcing the perceived legitimacy and social value of traffic regulations. These drivers may benefit from educational interventions that emphasize the collective benefits of rule compliance, demonstrate the real-world consequences of violations through case studies, and highlight the social contract inherent in shared road use. Research on traffic rules' perceived legitimacy [66,67] supports this approach, suggesting that when drivers view regulations as fair and necessary, compliance increases substantially.

Conversely, drivers exhibiting high Blame Externalization may require interventions targeting empathy development and perspective-taking skills. These individuals would benefit from programs that humanize other road users, emphasize shared vulnerability, and develop skills for taking personal responsibility. Virtual reality training scenarios could be particularly effective, allowing these drivers to experience road situations from the perspective of pedestrians, cyclists, or other vulnerable road users.

The MORDE scale can serve as a screening tool in driver education programs, enabling instructors to identify at-risk individuals and provide targeted interventions before problematic behaviors become entrenched. In rehabilitation programs for repeat offenders, the scale could help forensic psychologists develop individualized treatment plans, addressing the specific cognitive mechanisms underlying each person's risky driving behavior.

4.2. Advancing Sustainable Mobility Through Psychological Understanding

The MORDE scale addresses how individual attitudes and behaviors significantly influence the adoption of sustainable transport modes. by identifying psychological barriers to responsible mobility choices. High moral disengagement in driving contexts may create a cascade of effects that undermine sustainable transportation systems.

Drivers who morally disengage from traffic norms may be less likely to adopt eco-driving behaviors, such as maintaining steady speeds, planning efficient routes, or reducing unnecessary trips. The Normative Justification factor could predict resistance to environmental regulations, such as low-emission zones or congestion pricing, as these individuals may view such policies as illegitimate constraints on their driving behavior.

Furthermore, moral disengagement may impede the cultural shift necessary for sustainable mobility adoption. When drivers externalize blame for traffic problems (high Blame Externalization scores), they may resist transitioning to alternative transport modes, viewing cycling infrastructure or public transit investments as accommodating "others" rather than contributing to a collective transportation solution.

Urban planners and policymakers could use MORDE assessments to understand community readiness for sustainable mobility initiatives. Areas with high average moral disengagement scores might require more intensive education and engagement before implementing new sustainable transport policies, while communities with lower scores might be more receptive to immediate infrastructure changes.

The scale could also evaluate the effectiveness of sustainability campaigns. By measuring changes in moral disengagement before and after environmental awareness programs, transportation authorities could assess whether their initiatives successfully shift attitudes toward more responsible mobility choices.

4.3. Implications for Emerging Transportation Technologies

The MORDE scale has particular relevance for understanding human interactions with autonomous vehicles and advanced driver assistance systems (ADAS). Previous research has shown that moral disengagement can increase aggression toward autonomous vehicles [39,42], and our findings provide a framework for understanding these dynamics more precisely.

Drivers with high Normative Justification scores may resist automated systems that enforce traffic rules, such as intelligent speed adaptation or automated emergency braking, viewing these technologies as undermining their driving autonomy. They may attempt to circumvent or disable safety systems, potentially creating new safety risks. Understanding these tendencies can inform the design of human-machine interfaces that emphasize driver agency while maintaining safety benefits.

The Blame Externalization factor may predict how drivers interact with mixed traffic environments where autonomous and human-driven vehicles share the road. Drivers prone to externalizing blame may be more likely to engage in aggressive behaviors toward autonomous vehicles, blame these vehicles for traffic disruptions, or fail to adapt their driving behavior appropriately when interacting with automated systems.

As transportation systems evolve toward greater automation, the MORDE scale could help identify individuals who may struggle with these transitions. Targeted training programs could address specific moral disengagement patterns before drivers encounter new technologies on the road. For instance, drivers with high Blame Externalization scores might benefit from education about the collaborative nature of mixed traffic environments and the shared responsibility for safe interaction with automated systems.

The scale could also inform the development of adaptive automated systems that respond to different personality profiles. Vehicles equipped with ADAS might adjust their intervention strategies based on the driver's moral disengagement profile, providing more gentle guidance for individuals prone to normative justification while offering more explicit feedback for those who tend to externalize blame.

4.4. Broader Implications and Future Directions

Beyond these immediate applications, the MORDE scale addresses broader questions about moral behavior in technological contexts. As transportation becomes increasingly interconnected through vehicle-to-vehicle and vehicle-to-infrastructure communication, understanding how drivers morally engage with these systems becomes crucial for their successful implementation.

The distinction between the two moral disengagement dimensions can also be linked to recent studies on the perceived legitimacy of traffic norms [66,67]. One could hypothesize that a tendency to disengage from rules reflects a diminished perception of their legitimacy, whereas the justification of harmful behavior toward other drivers may be associated with processes of dehumanization or deindividuation typical of driving contexts. This hypothesis warrants further investigation, for instance by integrating instruments such as the Traffic Rules Perceived Legitimacy Scale with the MORDE, within longitudinal or experimental research designs.

Our results suggest that moral disengagement in driving can be understood as a multidimensional construct, consistent with a more refined view of moral self-regulation processes. This conceptualization opens the way for the development of targeted interventions, for example, educational strategies aimed at strengthening the perceived legitimacy of norms among those with high normative disengagement, or interventions fostering empathy and responsibility toward other road users among those with stronger relational disengagement.

4.5. Theoretical and Practical Implications

The MORDE scale can be used not only in scientific research but also as a screening or assessment tool in safe driving training programs, rehabilitation pathways for repeat offenders, or in forensic contexts. Moreover, it could prove useful for evaluating the effectiveness of educational or psychological interventions by measuring potential changes in moral disengagement levels before and after intervention. In this sense, the MORDE represents a flexible, theoretically grounded, and empirically validated tool capable of offering a concrete contribution to accident prevention and the promotion of prosocial driving behaviors.

Insurance companies might incorporate MORDE assessments into risk evaluation processes, potentially offering premium reductions for drivers participating in moral engagement training programs. Fleet managers could use the scale to identify employees who might benefit from additional safety training or closer monitoring. Driving schools could integrate MORDE assessments into their curricula, ensuring that new drivers develop appropriate moral engagement with traffic norms from the beginning of their driving careers.

4.6. Limitations and Future Directions

Some limitations of the present study should be acknowledged. Although the sample was large, it consisted mainly of young adults recruited online, which may limit the generalizability of the findings to other age groups. Indeed, this sample may present a young adult bias, limiting our findings from being applied to all drivers.

Nevertheless, it is worth noting that this age group represents one of the most involved in road accidents [1], making it a priority target for initial scale validation. Future studies should replicate the analyses on more diverse samples, including clinical or professional populations, to verify broader applicability. They will have to use stratified sampling across age groups (18–25, 26–45, 46–65, 65+) and supplement online recruitment with in-person recruitment. Furthermore, the exclusive use of self-report measures carries a risk of social desirability bias or limited metacognitive awareness. Future research should incorporate behavioral or implicit measures (e.g., driving simulations, naturalistic driving records) and validate the scale in cross-cultural contexts, considering that moral disengagement mechanisms may vary depending on the prevailing norms and social attitudes in different countries.

Another direction for future research involves exploring the relationships between the two MORDE dimensions and other relevant psychological constructs, such as empathy, risk perception, locus of control, personality traits, or metacognitive abilities. Nori et al. [68] have highlighted the role of theory of mind—particularly its cognitive component—in predicting risk perception and driving behavior. Targeted interventions aimed at developing this skill could therefore be beneficial, especially for novice drivers.

Finally, it would be useful to examine the temporal dynamics of moral disengagement in driving contexts: the mechanisms captured by the MORDE may not be stable traits but could fluctuate depending on situational factors such as stress, time pressure, or traffic conditions. The use of longitudinal or experience-sampling methodologies could shed light on the momentary variations and individual dynamics of moral disengagement over time.

5. Conclusions

The MORDE scale represents a significant advancement in the measurement of moral disengagement in driving contexts. Its bifactorial structure, empirically validated and theoretically anchored in Bandura's model, enables a deeper understanding of the cognitive and motivational mechanisms underlying risky driving behavior. In a historical moment in which road accidents continue to represent a serious global public health issue, tools such as the MORDE scale can contribute meaningfully to the understanding and prevention of dangerous conduct, offering new opportunities for research and targeted interventions in educational, clinical, and institutional settings.

Author Contributions: Conceptualization, P.C., L.P.; methodology, P.C., M.G., M.P., A.B., R.N.; validation, P.C., L.P., P.G., A.B., M.G., R.N.; formal analysis, P.C., M.G., M.P.; investigation, P.C., L.P., R.N., M.G., P.G., A.B.; resources, A.M.G.; data curation, P.C.; writing—original draft preparation, P.C., L.P.; writing—review and editing, P.C., L.P., A.B., P.G., R.N., M.G., M.P., A.M.G.; visualization, P.C., L.P., A.B., P.G., R.N., M.G., M.P., A.M.G.; supervision, P.C., L.P., A.M.G.; funding acquisition, A.M.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The Bioethics Committee and the Ethics Committee of the Department of Psychology, University of Bologna 61302 2021-03-15.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data supporting the findings of this study are available from the corresponding authors upon reasonable request. We are fully open to sharing the data with interested researchers, in compliance with applicable privacy and data protection regulations.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

MORDE	Moral Disengagement in Road Driving Evaluation
NJT	Normative Justification of Transgressive Driving
ABD	Attribution of Blame and Displacement of Responsibility
GMD	General Moral Disengagement
DBQ	Driver Behaviour Questionnaire
DAS	Driving Attitudes Scale
EFA	Exploratory Factor Analysis
CFA	Confirmatory Factor Analysis
RMSEA	Root Mean Square Error of Approximation
CFI	Comparative Fit Index
TLI	Tucker–Lewis Index

References

1. World Health Organization (WHO). Global Status Report on Road Safety. 2023. Available online: https://www.who.int/teams/social-determinants-of-health/safety-and-mobility/global-status-report-on-road-safety-2023 (accessed on 29 July 2025).
2. European Commission. Road Safety Statistics. 2023. Available online: https://transport.ec.europa.eu/background/road-safety-statistics-2023_en (accessed on 29 July 2025).
3. Campisi, T.; Moslem, S.; Duleba, S.; Tanbay, N.A.; Szmelter-Jarosz, A.; Tesoriere, G. Analysis of the effects of the first phase of COVID-19 pandemic on mobility choices in Italy by a multi-criteria approach. *Trans. Transp. Sci.* **2022**, *13*, 14–23. [CrossRef]
4. Zhang, G.; Yau, K.; Zhang, X.; Li, Y. Traffic accidents involving fatigue driving and their extent of casualties. *Accid. Anal. Prev.* **2016**, *87*, 34–42. [CrossRef]
5. Khan, K.; Zaidi, S.; Ali, A. Evaluating the nature of distractive driving factors towards road traffic accident. *Civ. Eng. J.* **2020**, *6*, 1555–1580. [CrossRef]
6. Saleem, S. Risk assessment of road traffic accidents related to sleepiness during driving: A systematic review. *East. Mediterr. Health J.* **2022**, *28*, 695–700. [CrossRef]
7. Piccardi, L.; Palmiero, M.; Guariglia, P.; Dacquino, C.; Cordellieri, P.; Giannini, A.M. Is the risk behaviour related to the ordinary driving violations? *Psychol. Stud.* **2021**, *66*, 283–290. [CrossRef]
8. Chou, S.P.; Dawson, D.A.; Stinson, F.S.; Huang, B.; Pickering, R.P.; Zhou, Y.; Grant, B.F. The prevalence of drinking and driving in the United States, 2001–2002: Results from the national epidemiological survey on alcohol and related conditions. *Drug Alcohol Depend.* **2006**, *83*, 137–146. [CrossRef] [PubMed]
9. Hingson, R.; Winter, M. Epidemiology and consequences of drinking and driving. *Alcohol Res. Health* **2003**, *27*, 63–78. [PubMed] [PubMed Central]
10. Saha, S.; Schramm, P.; Nolan, A.; Hess, J. Adverse weather conditions and fatal motor vehicle crashes in the United States, 1994–2012. *Environ. Health* **2016**, *15*, 104. [CrossRef]
11. Schlögl, M. A multivariate analysis of environmental effects on road accident occurrence using a balanced bagging approach. *Accid. Anal. Prev.* **2020**, *136*, 105398. [CrossRef]
12. Yang, G.; Ridgeway, C.; Miller, A.; Sarkar, A. Comprehensive assessment of artificial intelligence tools for driver monitoring and analyzing safety critical events in vehicles. *Sensors* **2024**, *24*, 2478. [CrossRef] [PubMed]
13. Schoeters, A.; Wijnen, W.; Carnis, L.; Weijermars, W.; Elvik, R.; Daniels, S.; Johannsen, H. Costs related to serious road injuries: A European perspective. *Eur. Transp. Res. Rev.* **2020**, *12*, 58. [CrossRef]
14. Ajzen, I. The theory of planned behavior. *Organ. Behav. Hum. Decis. Process.* **1991**, *50*, 179–211. [CrossRef]
15. Somoray, K.; White, K.; Watson, B.; Lewis, I. Predicting risky driving behaviours using the theory of planned behaviour: A meta-analysis. *Accid. Anal. Prev.* **2024**, *208*, 107797. [CrossRef] [PubMed]
16. Hafidy, A.; Rachad, T.; Idri, A. Understanding aberrant driving intentions based on the Theory of Planned Behavior: Literature review and meta-analysis. *J. Saf. Res.* **2024**, *90*, 225–243. [CrossRef] [PubMed]

17. Hai, D.; Minh, C.; Huynh, N. Meta-analysis of driving behavior studies and assessment of factors using structural equation modeling. *Int. J. Transp. Sci. Technol.* **2023**, *12*, 986–1003. [CrossRef]
18. Elliott, M.; Armitage, C.; Baughan, C. Using the theory of planned behaviour to predict observed driving behaviour. *Br. J. Soc. Psychol.* **2007**, *46*, 69–90. [CrossRef] [PubMed]
19. Rivis, A.; Sheeran, P. Descriptive norms as an additional predictor in the theory of planned behaviour: A meta-analysis. *Curr. Psychol.* **2003**, *22*, 218–233. [CrossRef]
20. Reynolds, C. The effects of moral judgment and moral identity on moral behavior: An empirical examination of the moral individual. *J. Appl. Psychol.* **2007**, *92*, 1610–1624. [CrossRef]
21. Parker, M.; Stradling, S. Extending the theory of planned behaviour: The role of personal norm. *Br. J. Soc. Psychol.* **1995**, *34*, 127–138. [CrossRef]
22. Chorlton, C.; Jamson, S. Identifying the psychological determinants of risky riding: An application of an extended Theory of Planned Behaviour. *Accid. Anal. Prev.* **2012**, *49*, 142–153. [CrossRef]
23. Conner, M.; Parker, D.; Manstead, A.S.R. Application of the theory of planned behaviour to the prediction of objectively assessed breaking of posted speed limits. *Br. J. Psychol.* **2007**, *98*, 429–453. [CrossRef]
24. Elliott, M.A. The social cognitive determinants of offending drivers' speeding behaviour. *Accid. Anal. Prev.* **2010**, *42*, 1595–1605. [CrossRef]
25. Benson, T.; McLaughlin, M.; Giles, M. The factors underlying the decision to text while driving. *Transp. Res. Part F Traffic Psychol. Behav.* **2015**, *35*, 85–100. [CrossRef]
26. Gauld, C.S.; Lewis, I.; White, K.M.; Fleiter, J.J.; Watson, B. Smartphone use while driving: What factors predict young drivers' intentions to initiate, read, and respond to social interactive technology? *Comput. Hum. Behav.* **2017**, *76*, 174–183. [CrossRef]
27. Kim, E. The role of legal and moral norms to regulate the behavior of texting while driving. *Transp. Res. Part F Traffic Psychol. Behav.* **2018**, *52*, 21–31. [CrossRef]
28. Moan, I.S. Predicting intentions not to "drink and drive" using an extended version of the theory of planned behaviour. *Accid. Anal. Prev.* **2011**, *43*, 1378–1384. [CrossRef]
29. Bailey, L.; Watson, B. Getting mad may not mean getting even: The influence of drivers' ethical ideologies on driving anger and related behaviour. *Transp. Res. Part F Traffic Psychol. Behav.* **2016**, *36*, 104–116. [CrossRef]
30. Du, S.; Chang, M.K. The exceptionists of Chinese roads: The effect of road situations and ethical positions on driver aggression. *Transp. Res. Part F Traffic Psychol. Behav.* **2018**, *58*, 719–729. [CrossRef]
31. Veldscholten, K. Moral Reasoning in Traffic: About the Possible Relations Between Moral Reasoning and Traffic Safety. Master's Thesis, University of Twente, Enschede, The Netherlands, 2015.
32. Bandura, A. Social cognitive theory of moral thought and action. In *Handbook of Moral Behavior and Development: Theory, Research and Applications*; Kurtines, W.M., Gewirtz, J.L., Eds.; Lawrence Erlbaum Associates: Hillsdale, NJ, USA, 1991; Volume 1, pp. 45–103.
33. Bandura, A.; Barbaranelli, C.; Caprara, G.; Pastorelli, C. Mechanisms of moral disengagement in the exercise of moral agency. *J. Personal. Soc. Psychol.* **1996**, *71*, 364–374. [CrossRef]
34. Zsolnai, L. Moral disengagement: How people do harm and live with themselves, by Albert Bandura. New York: Macmillan, 2016. 544 pp. ISBN: 978-1-4641-6005-9. *Bus. Ethics Q.* **2016**, *26*, 426–429. [CrossRef]
35. Ogunfowora, B.; Nguyen, V.N.; Steel, P.; Hwang, C.C. A meta-analytic investigation of the antecedents, theoretical correlates, and consequences of moral disengagement at work. *J. Appl. Psychol.* **2022**, *107*, 746–775. [CrossRef]
36. Bussey, K.; Luo, A.; Jackson, E. The role of moral disengagement in youth bullying behaviour. *Int. J. Psychol.* **2024**, *59*, 1254–1262. [CrossRef]
37. Boardley, I.; Kavussanu, M. Moral disengagement in sport. *Int. Rev. Sport Exerc. Psychol.* **2011**, *4*, 93–108. [CrossRef]
38. Zakharova, Y. Moral disengagement: Contemporary research, controversies and prospects. *J. Mod. Foreign Psychol.* **2025**, *14*, 5–15. [CrossRef]
39. Paschalidis, E.; Chen, H. Moral disengagement mechanisms in interactions of human drivers with autonomous vehicles: Validation of a new scale and relevance with personality, driving style and attitudes. *Transp. Res. Part F Traffic Psychol. Behav.* **2022**, *89*, 398–414. [CrossRef]
40. Cleary, J.; Lennon, A.; Swann, A. Should we be aiming to engage drivers more with others on-road? Driving moral disengagement and self-reported driving aggression. In Proceedings of the 26th Canadian Multidisciplinary Road Safety Conference, Quebec City, QC, Canada, 5–8 June 2016; Canadian Association of Road Safety Professionals: Quebec City, QC, Canada, 2016; pp. 1–16.
41. Toasin, M.; Endri, E. Driving self-control: A study of driving compliance behavior of the millennial generation. *Int. J. Innov. Res. Sci. Stud.* **2025**, *8*, 1894–1902. [CrossRef]
42. Liu, P.; Du, Y.; Wang, L.; Ju, D.Y. Ready to bully automated vehicles on public roads? *Accid. Anal. Prev.* **2020**, *137*, 105457. [CrossRef]

43. Umar, A.; Farooq, A. Anger on the road: Moderating role of trait emotional intelligence in the relationship between anger rumination and dangerous driving behaviors among young motorbike users. *Res. J. Soc. Aff.* **2025**, *3*, 28–40. [CrossRef]
44. Stephens, A.N.; Collard, J.; Koppel, S. Don't sweat the small stuff; anger rumination and lack of forgiveness are related to aggressive driving behaviours. *Curr. Psychol.* **2023**, *42*, 17264–17275. [CrossRef]
45. Basiyd-Fellahi, H.; Delhomme, P.; Cestac, J. Exploring the link between traffic violations and moral disengagement: A scoping review. *Transp. Res. Interdiscip. Perspect.* **2025**, *31*, 101438. [CrossRef]
46. Juniarly, A.; Effendi, E.K. Moral disengagement dan aggressive driving behavior: Tinjauan pada remaja pengendara sepeda motor. *Pers. J. Ilmu Psikol.* **2022**, *13*, 137–150. [CrossRef]
47. Ghiaskar, A.; Amiri, A.; Mirjalili, S. Polar fox optimization algorithm: A novel meta-heuristic algorithm. *Neural Comput. Appl.* **2024**, *36*, 20983–21022. [CrossRef]
48. Caprara, G.V.; Fida, R.; Vecchione, M.; Tramontano, C.; Barbaranelli, C. Assessing moral disengagement in youths. *Eur. J. Psychol. Assess.* **2006**, *22*, 105–111. [CrossRef]
49. Iversen, H.; Rundmo, T. Attitudes towards traffic safety, driving behaviour and accident involvement among the Norwegian population. *J. Risk Res.* **2004**, *7*, 377–397. [CrossRef]
50. Reason, J.; Manstead, A.; Stradling, S.; Baxter, J.; Campbell, K. Errors and violations on the roads: A real distinction? *Ergonomics* **1990**, *33*, 1315–1332. [CrossRef]
51. Smorti, M.; Guarnieri, S. Exploring the factor structure and psychometric properties of the Manchester Driver Behaviour Questionnaire (DBQ) in an Italian sample. *Test. Psychom. Methodol. Appl. Psychol.* **2016**, *23*, 185–202. [CrossRef]
52. Kaiser, H.F. An index of factorial simplicity. *Psychometrika* **1974**, *39*, 31–36. [CrossRef]
53. Bartlett, M.S. Properties of sufficiency and statistical tests. *Proc. R. Stat. Society Ser. A* **1937**, *160*, 268–282.
54. Horn, J.L. A rationale and test for the number of factors in factor analysis. *Psychometrika* **1965**, *30*, 179–185. [CrossRef]
55. Velicer, W.F. Determining the number of components from the matrix of partial correlations. *Psychometrika* **1976**, *41*, 321–327. [CrossRef]
56. Browne, M.W.; Cudeck, R. Alternative ways of assessing model fit. In *Testing Structural Equation Models*; Bollen, K.A., Long, J.S., Eds.; Sage: Newbury Park, CA, USA, 1993; pp. 136–162.
57. Hu, L.; Bentler, P.M. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Struct. Equ. Model.* **1999**, *6*, 1–55. [CrossRef]
58. Bentler, P.M.; Bonett, D.G. Significance tests and goodness of fit in the analysis of covariance structures. *Psychol. Bull.* **1980**, *88*, 588–606. [CrossRef]
59. Costello, A.B.; Osborne, J. Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Pract. Assess. Res. Eval.* **2005**, *10*, 1–9. [CrossRef]
60. Tabachnick, B.G.; Fidell, L.S. *Using Multivariate Statistics*, 7th ed.; Pearson: Boston, MA, USA, 2019.
61. Clark, L.A.; Watson, D. Constructing validity: New developments in creating objective measuring instruments. *Psychol. Assess.* **2019**, *31*, 1412–1427. [CrossRef]
62. DeVellis, R.F. *Scale Development: Theory and Applications*, 4th ed.; Sage: Thousand Oaks, CA, USA, 2017.
63. MacCallum, R.C.; Widaman, K.F.; Zhang, S.; Hong, S. Sample size in factor analysis. *Psychol. Methods* **1999**, *4*, 84–99. [CrossRef]
64. Cohen, J. *Statistical Power Analysis for the Behavioral Sciences*, 2nd ed.; Routledge: New York, NY, USA, 1988.
65. Swann, A.; Lennon, A.; Cleary, J. Development and preliminary validation of a scale of driving moral disengagement as a tool in the exploration of driving aggression. *Transp. Res. Part F Traffic Psychol. Behav.* **2017**, *46*, 124–136. [CrossRef]
66. Varet, F.; Granié, M.-A.; Carnis, L.; Martinez, F.; Pelé, M.; Piermattéo, A. The role of perceived legitimacy in understanding traffic rule compliance: A scoping review. *Accid. Anal. Prev.* **2021**, *159*, 106299. [CrossRef]
67. Varet, F.; Apostolidis, T.; Granié, M.-A. Social value, normative features and gender differences associated with speeding and compliance with speed limits. *J. Saf. Res.* **2023**, *84*, 313–323. [CrossRef] [PubMed]
68. Nori, R.; Zucchelli, M.M.; Cordellieri, P.; Quaglieri, A.; Palmiero, M.; Guariglia, P.; Giancola, M.; Giannini, A.M.; Piccardi, L. The prevention of road accidents in non-expert drivers: Exploring the influence of Theory of Mind and driving style. *Saf. Sci.* **2024**, *175*, 106516. [CrossRef]