ROAD AGGRESSION IN SIMULATED AND VIRTUAL DRIVING AND HUMAN-MACHINE INTERACTION: A SYSTEMATIC REVIEW AND BIBLIOMETRIC ANALYSIS

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Abstract

Road aggression is an important concern in traffic psychology, yet its study in virtual and simulated driving environments is complicated by inconsistent distinctions among aggression, anger, frustration, risky driving, and operationally defined aggressive driving styles. This systematic review and bibliometric analysis examined how aggression-related phenomena have been conceptualized, assessed, and investigated in virtual driving and human–machine interaction research. Searches of Scopus, Web of Science Core Collection, and APA PsycInfo yielded 134 records; after screening and eligibility assessment, 37 publications were included. Three findings were particularly relevant from a psychological perspective. First, driving anger, frustration, trait aggression, road rage, aggressive expression, and kinematically defined aggressive driving styles were related but non-equivalent constructs. Second, affective activation did not consistently correspond to risky or aggressive vehicle behavior: anger or trait aggression could be present without directly predicting behaviors such as risky passing or tailgating, supporting a distinction between internal state and behavioral expression. Third, several studies combined self-report and psychometric measures with behavioral, psychophysiological, and vehicle-dynamics indicators, suggesting the value of convergent multimodal assessment for construct validity. Virtual and simulated environments provide controlled conditions for examining aggression-related processes, but vehicle dynamics alone should not be interpreted as evidence of psychological aggression without supporting contextual, emotional, intentional, behavioral, or psychometric evidence. Future research should prioritize clearer construct definitions and validated multimodal assessment when developing adaptive human–machine systems.

Keywords: aggressive driving; driving anger; virtual reality; driving simulation; human–machine interaction.

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1. INTRODUCTION

Aggressive driving remains a concern in traffic psychology and road safety, although its conceptualization and operationalization vary. Aggression may encompass dispositional traits, driving anger, aggressive expression, interpersonal hostility, or vehicle-control patterns classified as aggressive driving styles (Bushman *et al.*, 2018). Speeding, tailgating, risky overtaking, and abrupt acceleration may reflect aggression, risk-taking, urgency, or driving preferences without necessarily indicating hostile intent.

Psychological aggression and risky driving are therefore distinct constructs. In simulated congestion, trait aggression and state anger were associated with confrontive coping but did not directly predict risky passing or tailgating (Emo *et al.*, 2016). This highlights the distinction between affective states, dispositions, aggressive expression, risky behavior, and operational driving styles. Vehicle dynamics alone cannot establish psychological aggression without contextual, affective, intentional, behavioral, or psychometric corroboration.

Virtual reality (VR), driving simulators, automated-driving environments, and human–machine interaction (HMI) paradigms enable controlled investigation of provocative traffic scenarios and associated psychological, behavioral, physiological, and vehicle-dynamics responses. Techer *et al.* (2017) combined electroencephalography (EEG) with simulated-driving performance to investigate anger-related attention and vehicle control. Immersive VR has examined pedestrian trust in automated vehicles with differing driving styles (Jayaraman *et al.*, 2018), while multimodal HMI approaches have addressed driving-related emotional regulation (Wei *et al.*, 2025). Nevertheless, the literature remains fragmented across construct definitions, experimental paradigms, technologies, and measurement strategies. Self-report, behavioral, psychophysiological, and vehicle-dynamics indicators capture complementary but non-equivalent responses. Their integration supports construct validity, as psychological activation does not necessarily correspond to aggressive or risky behavior. Automated-driving and adaptive HMI research further extends attention to driver–vehicle–technology interactions.

A systematic synthesis is needed to clarify aggression-related constructs, measures, and experimental approaches. This study integrates a systematic literature review with descriptive bibliometric and VOSviewer title-and-abstract term co-occurrence analyses. It examines technological environments, experimental scenarios, constructs, assessment, and interventions alongside temporal and thematic patterns, emphasizing distinctions between psychological aggression and operational driving risk and implications for VR/HMI research.

The research questions are:

RQ1. How has research representation changed across the publication period?

RQ2. Which technological environments, experimental scenarios, and methodological designs are represented?

RQ3. How are aggressive driving, anger, frustration, road rage, and aggressive driving styles conceptualized and operationalized?

RQ4. Which behavioral, psychophysiological, self-report, and vehicle-dynamics measures assess aggression-related responses?

RQ5. What thematic and temporal patterns characterize the literature, and what are their implications for adaptive VR/HMI assessment and intervention?

2. METHODOLOGY

REVIEW DESIGN AND SEARCH STRATEGY

This study integrated a systematic literature review with descriptive bibliometric and term co-occurrence analyses of aggression-related phenomena in virtual, simulated, and human–machine interaction driving research. The review examined aggression conceptualization, measurement, technological and experimental characteristics, and assessment or intervention approaches, while bibliometric analyses explored temporal and thematic patterns. Scopus, Web of Science Core Collection, and APA PsycInfo were systematically searched (final search: 28 August 2026) using aggression- and anger-related, driving, VR, simulation, automated-driving, and HMI and human–vehicle interaction (HVI) terms. Risky driving was distinguished from psychological aggression. Frustration was eligible as an aggression-related state but was not an independent primary search term; supplementary sensitivity searching identified no additional eligible publications. Database-specific strategies are provided in *Appendix A*. The protocol was not prospectively registered.

ELIGIBILITY CRITERIA AND PRISMA-BASED STUDY SELECTION

Eligible studies (a) examined driving, traffic, driver–vehicle, or road-user interactions; (b) investigated aggression, anger, hostility, road rage, or explicitly defined aggressive driving styles as substantive constructs, manipulations, outcomes, or interaction characteristics; and (c) employed virtual, simulated, automated-driving, HMI, or human–vehicle environments. Frustration-focused studies qualified when addressing aggression-related driving states, with supplementary sensitivity searching assessing omissions. Peer-reviewed journal and conference publications were included. Exclusions concerned studies addressing risk without aggression-related components, using aggressive solely as an engineering descriptor without relevant behavioral/HMI implications, or lacking eligible technological contexts. Vehicle-dynamics indicators (speed, acceleration, headway, time-to-collision, lateral-control variability) were insufficient to establish psychological aggression without contextual, emotional, intentional, behavioral, or psychometric corroboration.

Selection followed PRISMA 2020 identification, screening, retrieval, and eligibility stages (Page *et al.*, 2021). Title-and-abstract screening and report-level

eligibility were reviewed by three researchers, with uncertain cases resolved through collective discussion and consensus. Full-text exclusions and reasons are documented in *Appendix E*.

DATA EXTRACTION AND EVIDENCE SYNTHESIS

Structured extraction covered bibliographic and sample characteristics, design, technological setting, aggression-related constructs, scenarios, manipulations, psychological, behavioral, physiological and vehicle-dynamics outcomes, analytical methods, findings, limitations, and interventions. Data were extracted from available full texts; bibliographic information was verified against database records and publications, with abstracts supporting screening and verification. All three reviewers verified extracted fields and resolved discrepancies by consensus, without independent double extraction. Publications sharing datasets remained bibliographically distinct but were not treated as independent participant samples. Coding details appear in *Appendix B*. Heterogeneity in constructs, samples, settings, manipulations, and outcomes precluded meta-analysis. Narrative synthesis considered constructs, modalities, contexts, measurements, and assessment or intervention purposes, retaining null and mixed findings.

METHODOLOGICAL QUALITY AND RISK-OF-BIAS APPRAISAL

Methodological quality and risk of bias were assessed using design-appropriate Joanna Briggs Institute (JBI) checklists for randomized, quasi-experimental, and analytical cross-sectional studies. Computational model-development studies used a review-specific eight-domain framework addressing data, labels, features, validation, independence and leakage, preprocessing, performance metrics, and external validity. Simulation-only studies used another eight-domain framework covering scenarios, assumptions, comparators, replication or sensitivity, empirical validation, outcomes, analysis, and generalizability. These non-validated frameworks identified methodological strengths and limitations without overall classifications. Hybrid studies received JBI appraisal supplemented by computational criteria. Items were coded Yes, No, Unclear, or Not Applicable, supported by report-based evidence and page-level justification. All authors reviewed judgments and resolved disagreements by consensus; Unclear indicated insufficient reporting rather than necessarily high bias. For Mamo *et al.* (2026), the available preview supported eligibility and descriptive extraction, but insufficient methodological reporting prevented complete JBI appraisal. Items were not verifiable from the available report rated *Unclear* (*Appendix C*). Design-specific frameworks precluded aggregate quality scoring.

BIBLIOMETRIC AND TERM-NETWORK ANALYSIS

The bibliometric unit was the publication, not the independent participant sample. Publication years were analyzed descriptively, and title–abstract terms

mapped using VOSviewer 1.6.20 (van Eck & Waltman, 2010), with binary counting, a minimum occurrence of three, and retention of the default 60% most relevant eligible terms. No thesaurus was applied. Unavailable harmonized author-keyword metadata restricted analysis to title–abstract co-occurrence. Association-strength normalization, default layout settings (attraction = 2; repulsion = 1), clustering resolution 1.00, minimum cluster size 1, and small-cluster merging were used. VOSviewer assigned clusters, subsequently labeled by reviewers based on constituent terms. Network and temporal-overlay visualizations were examined descriptively. The overlay reflected average publication years of retained terms, indicating exploratory temporal variation rather than statistically tested change. Citation rankings, co-citation, and bibliographic coupling were excluded because reliable citation and cited-reference data were incomplete. Source dispersion was not used to establish a definitive core-journal structure owing to insufficiently standardized source metadata.

3. RESULTS

STUDY SELECTION AND CORPUS CHARACTERISTICS

The search identified 134 records (Scopus: 76; Web of Science Core Collection: 57; APA PsycInfo: 1). After removing 46 duplicates, 88 records were screened, of which 44 were excluded. Of 44 reports sought, four were unavailable for eligibility assessment. Three of the 40 assessed reports were excluded under predefined criteria, yielding 37 publications included in both the systematic review and bibliometric analysis (Figure 1). The 37 publications spanned 2016–2026, with annual counts of 4, 1, 6, 0, 1, 2, 1, 5, 8, 4, and 5, respectively. Most publications (22; 59.5%) appeared during 2023-2026, peaking in 2024. Bibliometric analyses treated publications as distinct documents, whereas multiple reports from the same dataset were not considered independent participant samples in the systematic synthesis.

METHODOLOGICAL QUALITY AND RISK-OF-BIAS RESULTS

Methodological appraisal reflected design heterogeneity. Twenty-two publications underwent JBI quasi-experimental assessment (two with computational/model-quality adjuncts), seven JBI randomized controlled trial assessment, and three JBI analytical cross-sectional assessment. Four model-development studies and one simulation-method study used corresponding structured quality frameworks. Recurring limitations included inadequate control or comparison conditions, repeated outcome measurement where applicable, participant blinding, and external model validation. *Unclear* judgments reflected insufficient reporting of retention, allocation concealment, blinding, baseline comparability, and computational independence or leakage control, rather than

necessarily high risk of bias. No pooled quality score was calculated because appraisal criteria differed by design. Study-level judgments appear in *Appendix C*.

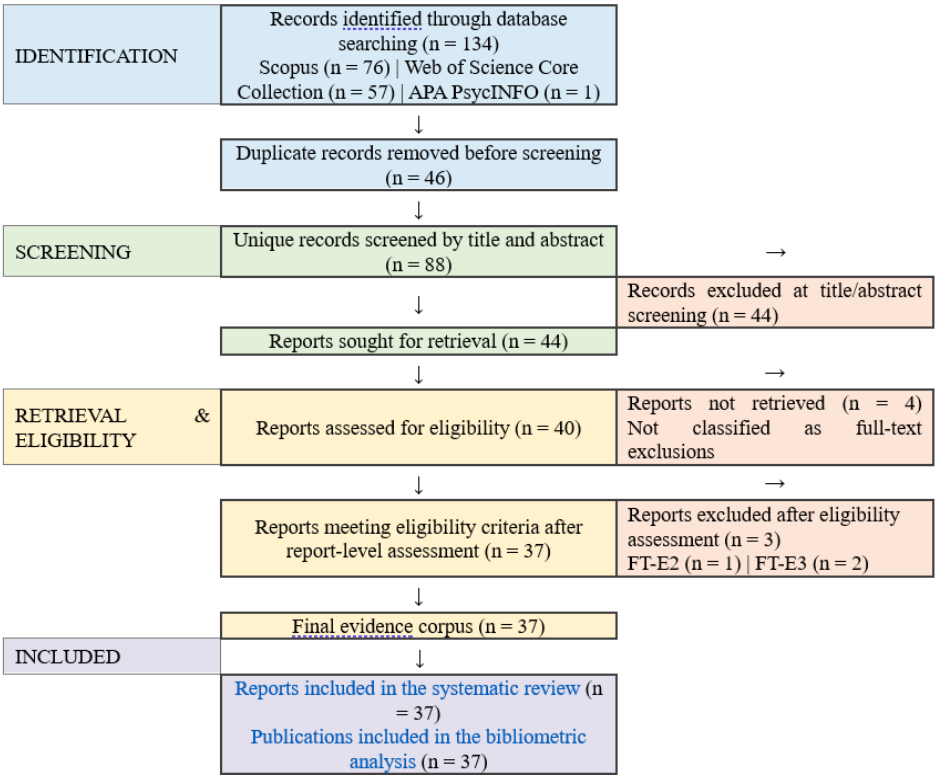


Figure 1. PRISMA flow diagram of study identification, screening, eligibility assessment, and inclusion.

Note. FT-E2 = aggressive driving primarily operationalized as an engineering/vehicle-profile characteristic without sufficient substantive alignment with the target aggression construct; FT-E3 = aggression-related construct not substantively linked to an eligible virtual, simulated, or HMI context. Final search: 28 August 2026.

TECHNOLOGICAL ENVIRONMENTS AND EXPERIMENTAL MODALITIES

The studies employed conventional simulators, immersive VR, automated-driving simulations, human-in-the-loop systems, web-based HMI/HVI experiments, and hybrid architectures, treated as distinct modalities. Scenarios involved congestion, repeated red lights, vehicle interference, honking, improper passing, pedestrian conflict, time pressure, hostile stimuli, and automated-vehicle behaviors. Outcomes included anger, frustration, aggressive expression, risk, trust, and road-user conflict. Examples included simulated congestion and risky passing

(Emo *et al.,* 2016), honking and improper passing in pedestrian encounters (Chai & Zhao, 2016), repeated anger-inducing events (Yan *et al.*, 2018), and reconstructed road-rage scenarios (Gu *et al*., 2026). Designs encompassed controlled experiments, randomized and non-randomized interventions, supervised web-based HMI experiments, observational and cross-sectional studies, and computational modeling. Automated-driving research also examined responses to defensive, normal, and aggressive vehicle styles (Jayaraman *et al.*, 2018; Peng *et al.*, 2024). Overall, RQ2 revealed substantial technological, experimental, and methodological diversity. As categories overlapped, their representation was characterized qualitatively rather than ranked by frequency.

CONCEPTUALIZATION OF AGGRESSION, ANGER, FRUSTRATION, AND RISKY DRIVING

Aggression-related constructs encompassed driving anger, frustration, road rage, trait aggression, aggressive expression, behavior, and operational driving styles. Anger and frustration reflected affective states, trait aggression an individual difference, and verbal, gestural, or interpersonal acts aggressive expression. Induced anger influenced attention and driving (Techer *et al.,* 2017), while trait aggression interacted with provocation in pedestrian encounters (Chai & Zhao, 2016). Frustration was assessed through subjective, behavioral, and physiological indicators (Ihme *et al*., 2018; Mamo *et al.,* 2026). Affect did not necessarily predict risky behavior: in simulated congestion, trait aggression and state anger were associated with confrontive coping but not directly with risky passing or tailgating (Emo *et al.,* 2016). In HMI and computational studies, aggressive driving styles represented vehicle-control patterns involving speed, acceleration, lane position, or temporal characteristics (Kwon *et al.,* 2021; Zhang *et al.,* 2026), without necessarily implying hostility or intent. Thus, RQ3 distinguishes affective states, dispositions, expressive behavior, and kinematic styles. Psychological aggression requires corroboration beyond vehicle dynamics through contextual, emotional, intentional, behavioral, or psychometric evidence. *Table 1* integrates these distinct measurement levels, indicators, and permissible inferences.

Table 1

Conceptual and Measurement Distinctions in Aggression-Related Driving Research

Level of analysis	**Constructs**	**Indicators / measures**	**Supported inference**	**Unsupported inference**
Affective state	Driving anger; frustration; road rage	Self-report; affect induction; EEG; electrodermal, cardiovascular, and facial activity	Aggression-related affect or activation	Overt aggression or risky driving
Dispositional characteristics	Trait aggression; anger propensity; individual differences	Psychometric and dispositional self-report measures	Aggression- or anger-related propensity	Current aggression or episode-specific behavior

Aggressive expression / conflict behavior	Confrontive responses; verbal, gestural, or interpersonal aggression	Comments; gestures; horn use; yielding; conflict responses	Observable aggression-related expression	Aggressive motive or intent without corroboration
Risk-related driving behavior	Risky passing; tailgating; unsafe overtaking; reduced safety margins	Overtaking; headway; safety gaps; time-to-collision; collisions	Behavioral or operational driving risk	Psychological aggression, anger, or hostility
Operational driving style	Aggressive; normal; cautious; defensive styles	Speed; acceleration; lane position; headway; temporal patterns; computational classification	Kinematic or operational driving profile	Psychological aggression, hostility, or intent

Note. Categories represent distinct but non-exclusive analytical levels; studies may combine indicators across levels. Vehicle dynamics indicate driving patterns or risk, not psychological aggression alone, which requires convergent contextual, affective, dispositional, behavioral, intentional, or psychometric evidence.

MEASUREMENT OF AGGRESSION-RELATED RESPONSES

Consistent with *Table 1*, four measurement domains emerged: self-report/psychometric, behavioral, vehicle-dynamics, and psychophysiological indicators. Self-report assessed anger, aggression, frustration, coping, trust, anxiety, comfort, and individual differences. Behavioral indicators included yielding, overtaking, horn use, collisions, verbal or gestural responses, and provocation-related behavior. Vehicle dynamics captured speed, acceleration/deceleration, headway, safety gaps, time-to-collision, lane position, deviation, and control. Psychophysiological measures included EEG, event-related potentials, electrodermal, cardiac, respiratory, facial-muscle, and ocular activity. Multimodal studies combined EEG with driving performance (Techer *et al.*, 2017), subjective anger with physiological and EEG responses (Yan *et al.*, 2018), frustration-related facial activity (Ihme *et al.*, 2018), and electrodermal, behavioral, and self-report indicators (Mamo *et al.*, 2026).

RQ4 revealed heterogeneous but frequently multimodal assessment. Subjective or physiological activation did not necessarily coincide with risky driving, highlighting the value of examining convergence and divergence across affective, behavioral, and driving-performance measures.

INTERVENTION AND EMOTION-REGULATION APPROACHES

A subset of studies examined cognitive-behavioral interventions, auditory feedback, olfactory stimulation, and multimodal HMI regulation targeting anger, frustration, or aggressive driving. Haustein *et al.* (2021) reported improved constructive anger expression, but non-significant reductions in several simulator-based aggressive-driving outcomes. Ota *et al.* (2024) found reduced self-reported frustration following slower false-heart-rate auditory feedback, without significant

driving changes. Olfactory findings varied: Moss *et al.* (2023) observed reduced aggressive driving under peppermint stimulation, while Wei and Shi (2025) identified scent-specific anger-modulation effects. Wei *et al.* (2025) reported improved affective outcomes using multimodal auditory–visual and auditory–olfactory HMI regulation following anger induction. However, heterogeneous intervention targets, measures, and designs limit generalization. Current evidence supports experimental regulation approaches but not a standardized, validated closed-loop system integrating real-time detection, intervention, and driving-safety outcomes.

BIBLIOMETRIC AND TERM-NETWORK RESULTS

Publication activity was uneven but concentrated in 2023–2026 (22 of 37; 59.5%), peaking in 2024 (n = 8). Recent studies increasingly addressed automated vehicles, trust, affect-aware interfaces, emotion regulation, and multimodal HMI. Given the small, purposefully delimited corpus, these patterns are descriptive, not statistical evidence of a field-wide temporal transition.

TERM CO-OCCURRENCE STRUCTURE

Title-abstract mining of 37 publications identified 1,248 terms, of which 91 met the minimum occurrence threshold of three. VOSviewer retained the 60% most relevant terms (n = 55), generating four clusters, 558 links, and a total link strength of 765. The clusters represented (1) emotion, provocation, and road safety; (2) aggression and behavioral operationalization; (3) automated vehicles and HMI; and (4) detection, methods, and intervention (*Figure 2 A, B*). These labels were assigned by the authors after algorithmic clustering, not predefined (see *Appendix D* for reproducibility).

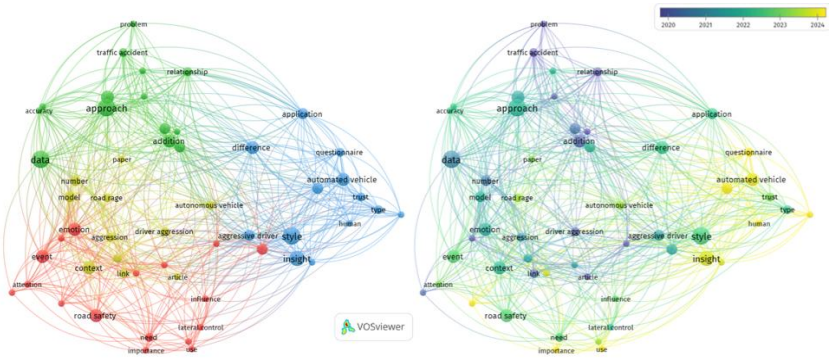


Figure 2. Term co-occurrence network and temporal overlay of the included literature.

A. Term co-occurrence network *B. Temporal overlay*

(A) Network of 55 VOSviewer-selected terms from 91 occurring at least three times across 37 publications (titles/abstracts), using binary counting and relevance selection. Four clusters, 558 links, and total link strength of 765 were identified. Node size indicates occurrence, links represent co-occurrence, and colors denote algorithmic clusters. (B) Temporal overlay showing average publication year per term, interpreted descriptively rather than as a statistical test of change.

The four areas addressed (1) anger, frustration, provocation, attention, and driving safety; (2) diverse aggression operationalizations, from psychological constructs and expression to driving styles; (3) automated vehicles, trust, and HMI/HVI interactions; and (4) methods, detection, modeling, and multimodal interventions. Term proximity indicated bibliometric co-occurrence, not conceptual equivalence. Thus, co-occurring psychological aggression and operational driving-style terms were not considered evidence of the same psychological construct.

TEMPORAL EVOLUTION OF THEMATIC EMPHASIS

The temporal overlay suggested earlier emphasis on emotion, attention, provocation, anger induction, and behavioral consequences, shifting toward automated vehicles, trust, adaptive HMI, and applications in later publications. This aligns with the descriptive synthesis, showing increased attention to automated driving, multimodal detection, and technology-mediated emotion regulation. However, the overlay reflects average publication years, not statistically tested trends, and cannot independently establish a disciplinary transition.

INTEGRATED FINDINGS ACROSS THE RESEARCH QUESTIONS

Across the five research questions, recent publications show broader representation of VR, automated driving, and HMI alongside simulator-based research on anger and behavior (RQ1). Platforms, scenarios, and designs remain diverse (RQ2). Aggression-related constructs differ across affect, disposition, expression, risk, and operational driving styles (RQ3), while assessment spans self-report, behavior, vehicle dynamics, and psychophysiology, often combining channels (RQ4). Four interconnected term clusters and the temporal overlay suggest greater recent attention to automated vehicles, detection, regulation, and HMI; temporal interpretations remain exploratory (RQ5).

4. DISCUSSION

The central conceptual contribution is distinguishing psychological aggression from risky driving. Anger, frustration, trait aggression, conflict behavior, and operational driving styles represent related but distinct constructs. Speeding, tailgating, acceleration, and risky overtaking do not independently establish hostility or intent. In simulated congestion, confrontive coping was more closely associated with risky maneuvers than trait aggression or anger (Emo *et al.*, 2016). Other studies assessed aggression through psychometrics, provocation, or behavioral expression (Ābele *et al.*, 2020; Chai & Zhao, 2016). Computational HMI studies often define aggressive driving styles through kinematic profiles (Kwon *et al.*, 2021; Zhang *et al*., 2026), which cannot establish psychological aggression without convergent evidence.

Aggression assessment requires distinguishing complementary but non-equivalent self-report, behavioral, psychophysiological, and vehicle-dynamics indicators. Multimodal simulator studies illustrate their potential divergence (Techer *et al.*, 2017; Yan *et al.*, 2018; Ihme *et al.*, 2018; Mamo *et al.*, 2026). Physiological activation may occur without risky driving, whereas risky maneuvers may reflect time pressure, cognitive load, sensation seeking, or driving preferences rather than aggression. Vehicle-dynamics classifiers identify operational patterns, not necessarily psychological states. Aggression-specific inference therefore requires contextual or psychological corroboration and independent external validation criteria.

Virtual and simulated environments enable standardized provocation and synchronized multimodal assessment. Interventions have examined cognitive-behavioral methods, auditory feedback, olfactory modulation, and multimodal HMI regulation (Haustein *et al.,* 2021; Moss *et al.*, 2023; Ota *et al.*, 2024; Wei & Shi, 2025; Wei *et al.,* 2025). However, methodological heterogeneity prevents conclusions about standardized effectiveness or validated closed-loop systems under naturalistic conditions. Adaptive systems must distinguish aggression from non-aggressive risk or arousal, deliver appropriate interventions, and demonstrate psychological and safety benefits. Automated-driving research further emphasizes interactions among driving style, trust, perceived appropriateness, and traffic context (Jayaraman *et al.*, 2018; Ma & Zhang, 2024b; Peng *et al.,* 2024). Bibliometric patterns suggest greater recent attention to automated vehicles, detection, regulation, and HMI, without establishing a field-wide transition. Several limitations qualify these findings. Studies varied in constructs, simulator fidelity, samples, designs, measures, and outcomes, with concerns regarding representativeness, comparison conditions, reporting, and model validation. Quality was assessed by methodological domain without pooled scores. The protocol lacked prospective registration; consensus verification replaced independent dual screening and extraction; and four reports remained inaccessible. Supplementary frustration-focused searching identified no additional eligible studies. Heterogeneity precluded meta-analysis, while shared datasets were not treated as independent samples. Incomplete citation metadata prevented robust citation-based analyses, and title–abstract mapping yielded descriptive rather than definitive bibliometric patterns. Reproducibility did not eliminate corpus-selection or text-mining limitations. Future research should clarify constructs, align measures with theoretical definitions, strengthen experimental controls, diversify samples, improve reporting, and externally validate computational models. Aggression-specific conclusions require convergent psychological, contextual, behavioral, psychophysiological, and vehicle-dynamics evidence. Longitudinal and naturalistic validation should establish real-world generalizability, while adaptive interventions must demonstrate reproducible psychological and driving-safety improvements.

5. CONCLUSION

This review synthesized 37 publications on aggression-related phenomena in virtual, simulated, and HMI driving settings. Psychological aggression is not equivalent to risky driving: anger, frustration, trait aggression, expression, risk behavior, and operational driving styles are distinct analytical levels. Speed, acceleration, headway, and safety margins cannot alone establish hostility or intent. Convergent self-report, psychometric, behavioral, psychophysiological, and vehicle-dynamics assessments can strengthen construct validity by identifying agreement or divergence among internal states and observable driving performance. This matters especially for computational systems that aim to infer psychological states rather than classify vehicle trajectories. VR, simulation, and HMI offer controlled platforms for such development, but current studies have not validated a real-world closed-loop system that reliably identifies aggression, differentiates non-aggressive risk, selects adaptive interventions, and demonstrates safety benefits. Future progress therefore depends on standardized construct definitions and outcome measures, theoretically grounded multimodal assessment, rigorous external validation, and evidence that findings obtained in controlled virtual or simulated environments generalize to naturalistic driving contexts.

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APPENDIX A

The complete database search strategies and study-selection information

Web of Science Core Collection	Scopus	APA PsycInfo
TS=((“aggressive driving” OR “driving aggression” OR “driver aggression” OR “road aggression” OR “road rage” OR “hostile driving” OR “driving anger”) AND (driv* OR driver* OR motorist* OR traffic OR vehicle*) AND (“virtual reality” OR “immersive virtual reality” OR “virtual environment*” OR “driving simulator*” OR “driving simulation” OR “simulated driving” OR “virtual driving” OR “immersive simulation” OR “human-machine interaction” OR “human machine interaction” OR HMI OR “human-vehicle interaction” OR “human vehicle interaction” OR “automated vehicle*” OR “autonomous vehicle*”))	TITLE-ABS-KEY((“aggressive driving” OR “driving aggression” OR “driver aggression” OR “road aggression” OR “road rage” OR “hostile driving” OR “driving anger”) AND (driv* OR driver* OR motorist* OR traffic OR vehicle*) AND (“virtual reality” OR “immersive virtual reality” OR “virtual environment*” OR “driving simulator*” OR “driving simulation” OR “simulated driving” OR “virtual driving” OR “immersive simulation” OR “human-machine interaction” OR “human machine interaction” OR HMI OR “human-vehicle interaction” OR “human vehicle interaction” OR “automated vehicle*” OR “autonomous vehicle*”))	(“aggressive driving” OR “driving aggression” OR “driver aggression” OR “road aggression” OR “road rage” OR “hostile driving” OR “driving anger”) AND (driv* OR driver* OR motorist* OR traffic OR vehicle*) AND (“virtual reality” OR “immersive virtual reality” OR “virtual environment*” OR “driving simulator*” OR “driving simulation” OR “simulated driving” OR “virtual driving” OR “immersive simulation” OR “human-machine interaction” OR “human machine interaction” OR HMI OR “human-vehicle interaction” OR “human vehicle interaction” OR “automated vehicle*” OR “autonomous vehicle*”)

Note. A supplementary sensitivity search combined frustration-related terms with the primary driving and virtual/simulated/HMI domains to identify eligible studies indexed under frustration rather than aggression or anger. No additional eligible publications were identified.

APPENDIX B

Compact study-level empirical synthesis (N = 37)

Study	Design / context	Main empirical finding
1. Zhu *et al.* (2026)	CAV styles; CARLA	Cautious mode preferred; position/intervention effects.
2. Gu *et al.* (2026)	Road rage; audiovisual simulation	Anger induced; slow onset, rapid decay.
3. Mamo *et al.* (2026)	Frustration; simulator/EDA	Higher EDA and some safer responses in autistic drivers.
4. Zhang *et al.* (2026)	Driving styles; ML	Context-dependent styles; 36% transitions.
5. Wei & Shi (2025)	Anger; scents	Jasmine/lemongrass beneficial; peppermint/patchouli adverse.
6. Wei *et al.* (2025)	Anger; multimodal HMI	Improved affective ratings.
7. Maillant *et al.* (2025)	Anger triggers; automation	Combined triggers increased anger; weak physiological differentiation.
8. Usama *et al.* (2025)	ADAS; cyclist overtaking	Greater benefits for passive drivers; age-related variability.
9. Ma & Zhang (2024b)	AV maneuvers; trust	Unexpected maneuvers reduced trust/acceptance.
10. Hong & Abbas (2024)	Traffic co-simulation	Linked aggressive driving changes to traffic conflicts.
11. Peng *et al.* (2024)	AV styles; comfort	Defensive style preferred; sensation-seeking effects.
12. Ma & Zhang (2024a)	HV–AV/HV–HV interactions	Aggressive/moderate drivers: greater discomfort/aggression.
13. Ota *et al.* (2024)	Frustration; heart-rate audio	Slow feedback reduced frustration; driving unaffected.
14. Su *et al.* (2024)	Trait anger; AV gaps	Short gaps impaired control; medium gaps moderated responses.
15. Muhundan & Jeon (2024)	L3 AV; agent language	Native language improved awareness, performance and preference.
16. Wang & Jeon (2023)	Anger intensity; simulator	Low anger linked to speeding; impaired lateral control.
17. Dominguez *et al.* (2023)	Emotion/styles; EV	Profiles distinguishable; aggression reduced driving range.
18. Zhang *et al.* (2023)	Mixed traffic; time pressure	Aggressive style/pressure increased aggressive decisions.
19. Moss *et al.* (2023)	Peppermint; VR	Reduced aggressive driving; variable mood effects.
20. Wu *et al.* (2023)	Cognitive/penalty feedback	Penalty/combined feedback reduced some speeding indicators.
21. He *et al.* (2022)	Anger; day/night turns	Shorter accepted gaps/PET under anger and nighttime conditions.
22. Chen *et al.* (2024)	Affective HMi	Improved self-reported emotional state.
23. Kwon *et al.* (2021)	CNN–LSTM; V2X	Accurate style detection; increased TTC with V2X.
24. Haustein *et al.* (2021)	Group CBT; simulator	Improved constructive expression; nonsignificant simulated changes.

25. Ābele *et al.* (2020)	Anger; DAX/DBQ	Verbal/gestural anger associated with aberrant-driving reports.
26. Ihme *et al.* (2018)	Frustration; facial EMG	Increased mouth-region muscle activity.
27. Jayaraman *et al.* (2018)	AV styles; pedestrian trust	Trust affected mainly at unsignalized crossings.
28. Bushman *et al.* (2018)	Narcissism; simulation	Positive association with aggression (mean r = .35).
29. Brodsky *et al.* (2018)	Music; simulator	Energetic music impaired lateral control; hostile lyrics increased speed.
30. Techer *et al.* (2017)	Anger; EEG/simulator	Greater lateral variability; reduced visual N1.
31. Emo *et al.* (2016)	Congestion; anger/coping	Confrontive coping predicted risk; anger lacked direct effects.
32. Biassoni *et al.* (2016)	Anger; reappraisal	Anger increased violations; reappraisal reduced them.
33. Qu *et al.* (2016)	Trait anger/expression	Trait anger linked to speed; expression more to crashes.
34. Chai & Zhao (2016)	Provocation; yielding	Less yielding and closer pedestrian approaches.
35. Yan *et al.* (2018)	Anger; EEG/BVP/EDA	Anger detection accuracy: 85%.
36. Wang *et al.* (2026)	Anger intensity; ML	Two-stage classification superior; accuracy up to .90.
37. Braly *et al.* (2018)	Masculinity threat; overtaking	Increased anger; no significant overtaking effect.

Abbreviations. ACC = adaptive cruise control; ADAS = advanced driver-assistance systems; AV = automated vehicle; BVP = blood volume pulse; CARLA = Car Learning to Act; CAV = connected and automated vehicle; CBT = cognitive behavioral therapy; CNN–LSTM = convolutional neural network–long short-term memory; DAX = Driving Anger Expression Inventory; DBQ = Driver Behaviour Questionnaire; EDA = electrodermal activity; EEG = electroencephalography; EMG = electromyography; EV = electric vehicle; HMi = human–machine interface; HV = human-driven vehicle; ML = machine learning; PET = post-encroachment time; TTC = time to collision; V2X = vehicle-to-everything; VR = virtual reality.

APPENDIX C

Methodological quality and risk-of-bias appraisal

Study	Appraisal framework	Yes	No	Unclear	N/A
1. Zhu *et al.* (2026)	JBI-QE	7	1	1	0
2. Gu *et al.* (2026)	JBI-QE+M	12	2	1	2
3. Mamo *et al.* (2026)	JBI-QE	0	0	9	0
4. Zhang *et al.* (2026)	MDQ	7	1	0	0
5. Wei & Shi (2025)	JBI-QE	8	0	1	0
6. Wei *et al.* (2025)	JBI-QE	8	0	1	0
7. Maillant *et al.* (2025)	JBI-QE	8	0	1	0
8. Usama *et al.* (2025)	JBI-QE	8	0	1	0
9. Ma & Zhang (2024b)	JBI-QE	7	1	1	0
10. Hong & Abbas (2024)	SMQ	6	1	1	0
11. Peng *et al.* (2024)	JBI-QE	6	2	1	0

12. Ma & Zhang (2024a)	JBI-QE	6	2	1	0
13. Ota *et al.* (2024)	JBI-QE	7	1	1	0
14. Su *et al.* (2024)	JBI-QE	6	2	1	0
15. Muhundan & Jeon (2024)	JBI-QE	8	0	1	0
16. Wang & Jeon (2023)	JBI-RCT	7	2	4	0
17. Dominguez *et al.* (2023)	MDQ	6	1	1	0
18. Zhang *et al.* (2023)	JBI-QE	6	2	1	0
19. Moss *et al.* (2023)	JBI-RCT	8	1	4	0
20. Wu *et al.* (2023)	JBI-RCT	9	1	3	0
21. He *et al.* (2022)	JBI-RCT	8	1	4	0
22. Chen *et al.* (2024)	JBI-RCT	8	1	4	0
23. Kwon *et al.* (2021)	MDQ	6	0	2	0
24. Haustein *et al.* (2021)	JBI-QE	8	0	1	0
25. Ābele *et al.* (2020)	JBI-ACS	6	0	0	1
26. Ihme *et al.* (2018)	JBI-QE	8	0	1	0
27. Jayaraman *et al.* (2018)	JBI-QE	6	2	1	0
28. Bushman *et al.* (2018)	JBI-ACS	6	0	0	1
29. Brodsky *et al.* (2018)	JBI-QE	7	1	1	0
30. Techer *et al.* (2017)	JBI-QE	8	0	1	0
31. Emo *et al.* (2016)	JBI-QE	7	1	1	0
32. Biassoni *et al.* (2016)	JBI-RCT	8	1	4	0
33. Qu *et al.* (2016)	JBI-ACS	5	0	1	1
34. Chai & Zhao (2016)	JBI-QE	7	1	1	0
35. Yan *et al.* (2018)	JBI-QE+M	14	0	3	0
36. Wang *et al.* (2026)	MDQ	6	1	1	0
37. Braly *et al.* (2018)	JBI-RCT	9	0	4	0
Total - 37 publications / 366 item-level judgments		267	29	65	5

Note. JBI-QE = Quasi-Experimental; JBI-QE+M = Quasi-Experimental with model-quality adjunct; JBI-RCT = Randomized Controlled Trial; JBI-ACS = Analytical Cross-sectional; MDQ = Model-Development Quality Audit; SMQ = Simulation-Model Quality Audit. Yes/No = criterion met/unmet; Unclear = insufficient information; N/A = not applicable. Counts reflect item-level judgments, not quality scores, and are not directly comparable or aggregable across frameworks.

APPENDIX D

VOSviewer Analysis Parameters and Cluster Interpretation

Parameter	Setting	Parameter	Setting
Software	VOSviewer 1.6.20	Normalization	Association strength
Source	Titles/abstracts	Attraction/repulsion	2/1
Counting	Binary	Clustering resolution	1.00
Min. occurrences	3	Min. cluster size	1
Initial terms	1,248	Clusters	4
Eligible terms	91	Links	558
Relevance retained	60%	Total link strength	765
Final terms	55	Thesaurus	None

Note. Clusters were generated algorithmically; labels reflect authors' interpretation. Term co-occurrence does not imply conceptual equivalence between psychological aggression, driving risk, and operational driving styles.

APPENDIX E

Study-selection audit trail. Reports excluded after full-text eligibility assessment

Report	Exclusion code	Reason for exclusion
Zhu *et al.* (2017), doi	FT-E2	Focused on VSP-based stop-and-go behavior and emissions. Aggression was operationalized as a driving profile, not a psychological/HMI construct; relevant only to vehicle-dynamics interpretation.
Tsoutsi *et al.* (2019), doi	FT-E3	Simulator assessed driving performance in depression; aggression was a separate self-reported correlate, not a focal simulator construct. Retained as background evidence only.
Ortiz-Peregrina *et al.* (2021), doi	FT-E3	Simulator assessed substance-related visual function and vehicle dynamics. Aggression was primarily DDDI self-reported, without aggression-specific simulator manipulation or outcome.

Note. FT-E2 = engineering/vehicle-profile definition without substantive psychological aggression relevance; FT-E3 = insufficient aggression-related relevance to eligible virtual, simulated, or HMI contexts. These were the only three full-text exclusions; four unretrieved reports were not assessed for eligibility.