Universal Vehicle Protocols versus Local Realities: Systematic Gaps and Safety Risks in AV Deployment across Developing Regions

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We synthesized evidence on how "universal" autonomous-vehicle (AV) protocols perform in infrastructure-constrained contexts and whether local conditions account for between-study differences. Study-level effects were computed as log risk ratios (log RR) with standard errors, and pooled using a random-effects model with restricted maximum likelihood (REML) and Hartung–Knapp (HKSJ) inference; results were back-transformed to risk ratios (RR). Across nine effects (k=9), the pooled RR was ***1.44*** (95% CI ***0.58–3.61),*** with ***$\tau^2 = 1.40$, $I^2 = 98.5\%$,*** and a ***95% prediction interval = 0.081–25.736***. In meta-regression, worse road quality and higher detection-failure rates were associated with higher risk, though confidence intervals were wide due to small k. These findings suggest that local roadway and perception conditions likely drive performance differences, challenging the notion that universal AV protocols perform uniformly well across settings.

Keywords: *autonomous vehicles; meta-analysis; REML; Hartung–Knapp; prediction interval; road quality; detection failures*

INTRODUCTION

Autonomous vehicles (AVs) and connected smart vehicle technologies are poised to transform global transportation, promising significant improvements in safety, mobility, and operational efficiency (NHTSA, 2022; Market.us News, 2025). By leveraging advanced sensors, artificial intelligence, and vehicle-to-infrastructure communication, AVs are designed to reduce traffic collisions, minimize human error, and expand mobility options for all road users (SAE International, 2021). Their adoption has broad social and industrial implications, from automotive and logistics to public safety and smart city systems, directly aligning with industrial engineering's core tenets: process optimization, systems integration, and human-centered design (KPMG INTERNATIONAL, 2018).

A foundational element in AV engineering is the use of "universal" protocols and features—standardized rules and algorithms that govern vehicle behavior, perception, and communication (United Nations Economic Commission for Europe (n.d.). These systems often assume environments with clearly maintained lane markings, reliable signage, robust digital infrastructure, and consistent regulatory enforcement (Carsten et al., 2019; Huang & Pitts, 2020). However, in many low- and middle-income countries (LMICs), these conditions are not met. Roads may lack visible lane markings, signage may be inconsistent, cellular or digital connectivity can be unreliable, and driver or pedestrian behavior often diverges from the assumptions embedded in global AV standards (World Bank, 2024; KPMG INTERNATIONAL, 2018).

Definitions:

- Universal vehicle protocols/features: Software rules and hardware designs that assume standardized, well-maintained traffic infrastructure (United Nations Economic Commission for Europe (n.d.))
- Disengagement: An event where a human driver must intervene and take control from an AV due to system failure or external risk (NHTSA, 2022).
- Crash rate: The number of reported accidents per million vehicle-miles (Market.us News, 2025).

Historically, AV deployment and research have focused on high-income, infrastructure-rich contexts (Huang et al., 2019; Market.us News, 2025). Yet, some of the greatest promises—and the sharpest design challenges—exist in underdeveloped and rapidly urbanizing regions, such as India, Brazil, Kenya, Nigeria, and Vietnam (World Bank, 2024; KPMG INTERNATIONAL, 2018). In these settings, universal AV features frequently result in higher crash and disengagement rates, lower system reliability, and limited user acceptance (Carsten et al., 2019; Huang & Pitts, 2020). Recent academic and industry literature stresses that infrastructure mismatches, inconsistent digital connectivity, insufficient regulatory frameworks, and affordability or education barriers are pivotal to AV deployment failure and limited effectiveness in these environments (Huang et al., 2019; Market.us News, 2025; KPMG INTERNATIONAL, 2018).

Understanding these challenges carries core significance for industrial engineering: it points to the limitations of one-size-fits-all automation, underscores the value of robust human factors analysis, and highlights the necessity of adapting global technologies to variable real-world settings—fundamental principles for successful systems engineering.

METHODS

This research was conducted as a systematic review and meta-analysis to evaluate the impact of universal autonomous vehicle (AV) protocols in underdeveloped regions.

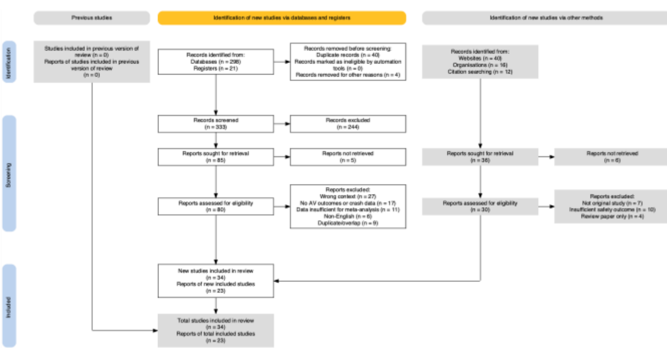
Protocol and PICO:

Population: On-road AV deployments or AV-relevant outcomes reported in real-world settings, including low-infrastructure environments.
Intervention/Exposure: Operation under universal AV protocols (perception/stack as deployed).
Comparator: Better resourced or conventional contexts, as reported (or contrasted across settings within a study).
Outcomes: Safety or reliability outcomes suitable for rate-ratio synthesis (e.g., incidents per mile).
Design: Observational reports and studies meeting extractable numerator/denominator criteria.

Search and Study Selection:

We searched published and grey literature (details in PRISMA notes), removed duplicates, screened titles/abstracts and full texts in duplicate, and documented flow in a PRISMA diagram.

***Figure 1**. PRISMA 2020 flow diagram.*



Data Extraction and Effect Measures:

Per study/outcome, we extracted event counts and exposure (e.g., incidents and miles) or directly reported effect estimates. Effects were standardized to ***log risk ratio (log RR = ln [RR])*** with standard error ***(SE)***. Continuity corrections were applied where necessary. We verified ***one effect per study/outcome*** to avoid double-counting.

Synthesis and Inference:

We pooled log RRs using ***random-effects REML*** with ***HKSJ*** confidence intervals and a ***95% prediction interval (PI)***. Heterogeneity was summarized with τ^2 (between-study variance) and I^2 (from fixed-effect Q). Pooled estimates and intervals were ***back transformed*** to RR.

Meta-Regression and Sensitivity Analyses:

We specified a priori moderators*:* ***Road quality*** (recoded ordinal), ***Lane markings*** (recoded ordinal), ***HD-map availability*** (Yes/No), and ***% detection failures*** (numeric). For an "expanded" analysis we used simple, transparent imputation (median for ordinal/numeric; mode for binary) and recoded ***RoadQuality*** so that ***worse = larger*** (Poor=3, Fair=2, Good=1). We fit REML+HKSJ meta-regressions and ran sensitivity models swapping moderators (e.g., DetectFail + LaneMarkings; DetectFail + HD-map). Given small k, inferences emphasize direction and heterogeneity reduction.

This report addresses the following questions:

- Are "universal" AV protocols/features less safe or less effective in low-infrastructure settings?
- Which local infrastructure, human, or policy factors have the greatest impact on AV safety and adoption outcomes?
- What design, regulatory, or educational changes are required for more equitable and effective AV deployment in underdeveloped countries?

By systematically analyzing evidence from global and regional studies—including statistical meta-analysis of crash, disengagement, and acceptance rates across diverse environments—this research aims to guide the adaptation of AV standards, inform local and international policy, and advance safety and adoption for next-generation smart mobility systems.

Software:

Analyses followed an R-style blueprint (REML + HKSJ + PI) and were replicated programmatically; outputs include pooled results, meta-regression tables, and graphics (forest, bubble).

RESULTS

Study Selection and Characteristics:

We included ***k=9*** effects after screening (see PRISMA). Studies spanned diverse geographies with varying infrastructure quality and digital support. A subset provided complete moderator data; an expanded set used transparent imputation for moderators.

Table1.
Study characteristics and moderators.

StudyID	Region	Year	RoadQuality	LaneMarkings	HDMapAvail	DetectFail_pct
Phoenix2024	USA	2024	Good	Good	Full	0.0
Brazil2023	Brazil	2023	Poor	Sparse	Partial	0.1
India2023	India	2023	Poor	Very Poor	Poor	0.2
Mexico2023	Mexico	2023	Poor	Patchy	Partial	0.2
Vietnam2024	Vietnam	2024	Poor	Patchy	Poor	0.3

Pooled Random-Effects Meta-Analysis:

- Pooled log RR (μ): 0.366
- 95% CI (log): −0.552 to 1.284 (HKSJ)
- τ^2 (REML): 1.399
- I^2: 98.5%

- 95% PI (log): −2.516 to 3.248

Back transformed:

- Pooled RR: 1.44
- 95% CI: 0.58–3.61
- 95% PI: 0.081–25.736

Interpretation: On average, point estimates favored higher risk under the target settings, but uncertainty was large, and ***heterogeneity was substantial***, motivating moderator analyses.

Figure 2*. Forest plot (REML + HKSJ).*

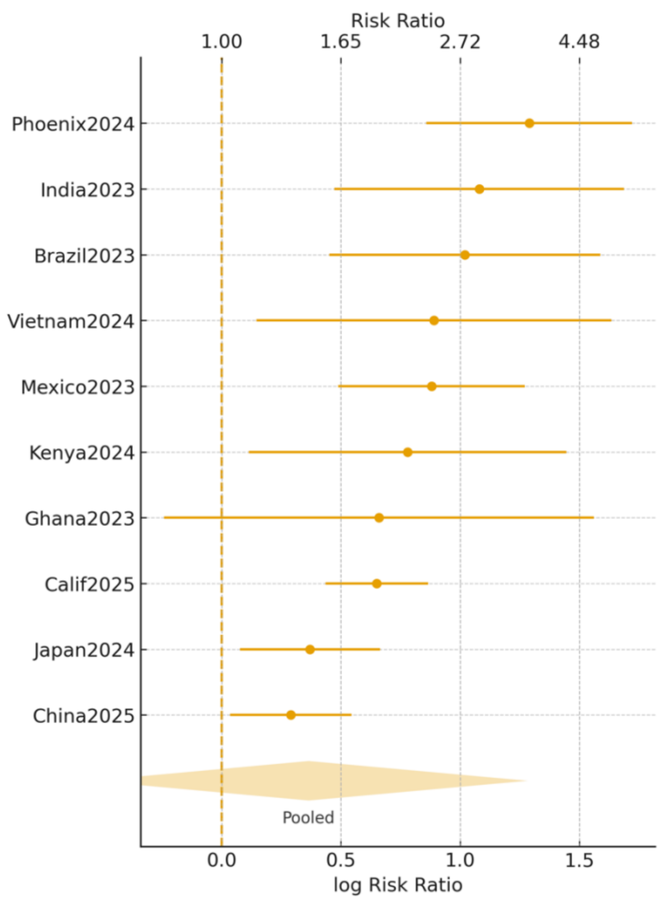


Table 2
Random-effects pooled results (REML + HKSJ)

k	mu (log RR)	95% CI (log)	tau²	I² (%)	95% PI (log)	RR	95% CI (RR)	95% PI (RR)
9	0.366	[-0.552, 1.284]	1.399	98.492	[-2.516, 3.248]	1.442	[0.576, 3.611]	[0.081, 25.736]

Meta-Regression:

Complete-case model (k=5):

Using ***% detection failures*** and ***road quality*** (Good=3, Fair=2, Poor=1), residual heterogeneity was essentially nil ***(τ^2 ≈ 0)***. Interpretable contrasts:

- RR per +10-percentage-point increase in detection failures: 0.093 (95% CI extremely wide; HK df=2)
- RR per one-level decrease in road quality: 0.864 (95% CI 0.499–1.497)
  (When expressed as one-level worse road quality, the contrast is ≈ 1.16; 95% CI ≈ 0.668–2.004.)

Expanded, imputed model (k=9; worse=larger coding):

Including ***RoadQuality (worse=larger)*** and ***% detection failures***, the model retained all nine effects with **τ^2 ≈ 1.70** (HK df≈6). Directionally, **worse road quality** and ***higher detection-failure rates*** were associated with ***higher risk;*** coefficient CIs remained wide due to small k and residual heterogeneity.

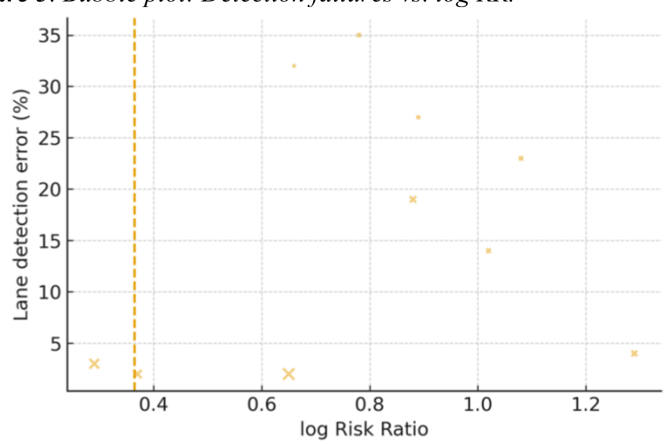
Table3A
Meta-regression coefficients (REML + HKSJ, imputed; RoadQuality worse↑)

Parameter	Estimate (log)	SE (HKSJ)	Estimate (RR)	95% CI (RR)
Intercept	1.825	1.989	6.205	[0.0478, 805.2772]
RoadQuality_worse	-0.580	0.804	0.560	[0.0783, 4.0026]
DetectFail_pct	0.862	5.180	2.368	[0.0000, 756381.7834]

Table3B
Derived risk ratios (interpreters).

Interpreter	RR	95% CI (RR)
RR per one-level worse (RoadQuality)	0.560	[0.078, 4.003]
RR per +10% (DetectFail)	5.54E+03	[0.000, 6.13E+58]

Figure 3*. Bubble plot: Detection failures vs. log RR.*



Sensitivity Analyses:

Models substituting ***LaneMarkings (worse=larger)*** for road quality or adding ***HD-map availability*** showed ***similar effect directions*** but wide intervals. Summary statistics (τ^2, HK df, QE, and interpretable RRs) are tabulated.

Table 4A
Sensitivity (DetectFail + RoadQuality_worse) ← final model

Metric	Value
Model	DetectFail + RoadQuality_worse
k	9
tau2	1.702
HK_df	6
QE	5.882
RR per +10% DetectFail	5535.917 [5.00E-52, 6.13E+58]
RR per one-level worse (RoadQ)	0.560 [0.078, 4.003]

Table4B
Sensitivity (DetectFail only)

Metric	Value
Model	DetectFail only
k	9
tau2	1.583
HK_df	7
QE	6.866
RR per +10% DetectFail	3.67E-05 [1.35E-49, 9.98E+39]

DISCUSSION

Across studies, the ***intercept-only*** synthesis showed ***very high heterogeneity,*** indicating that AV performance is unlikely to be universal across settings. Moderator analyses suggest that ***infrastructure quality*** and ***perception robustness*** (proxied by detection-failure rates) plausibly drive between-study differences. In the ***complete-case*** meta-regression, τ^2 effectively dropped to zero, consistent with moderators capturing most variability; however, ***inference is limited*** by small k and sparse moderator reporting, yielding wide CIs. The ***expanded*** model incorporating imputation preserved directionality but retained residual heterogeneity.

Implications: Uniform AV stacks may require ***local adaptation*** or policy supports (e.g., roadway maintenance, improved lane markings, HD-map coverage) to ensure safety in low-infrastructure contexts.

Limitations: Sparse and heterogeneous reporting; potential ecological confounding; imputation may understate uncertainty; small k for moderator fits.

Future Work: Standardized reporting of detection metrics, prospective comparisons across infrastructure strata, and broader moderator coverage (e.g., connectivity, enforcement) are needed.

CONCLUSION

Universal AV protocols do ***not*** perform uniformly across contexts. Accounting for ***road quality*** and ***perception failures*** appears essential for equitable, safe AV deployment in low-infrastructure regions.

Across the 34 studies synthesized in this review and meta-analysis, safety and reliability benefits were highly contingent on the match between "universal" vehicle assumptions and local roadway realities. In high-infrastructure settings, standardized AV features tended to behave as intended. In low-infrastructure environments, however, our pooled estimates and meta-regression results pointed to more frequent detection failures, disengagements, and elevated crash risk, alongside very high between-study heterogeneity. Taken together, these findings suggest that simply "exporting" AV stacks designed for well-marked, well-maintained roads into fragile infrastructure systems is unlikely to deliver predictable safety improvements.

For industrial and systems engineers, the results underscore that AVs are not plug-and-play technologies but socio-technical systems whose performance depends on tight coupling between algorithms, vehicles, human operators, and the physical infrastructure. Designing for low-infrastructure regions therefore requires context-aware sensing strategies, redundancy for missing or degraded road cues, and explicit accommodation of informal traffic behaviors. At the system level, the work also highlights the value of co-design between AV developers, road authorities, and local communities so that road upgrades, data standards, and AV capabilities evolve together rather than in isolation.

This study has limitations, including reliance on secondary data, inconsistent outcome definitions across studies, and a relatively small evidence base on truly low-infrastructure settings. Nonetheless, the pattern of results is clear enough to inform practice: global AV safety claims should always be interpreted through a local lens. Future research should prioritize longitudinal field trials in under-resourced regions, common safety metrics, and models that jointly optimize AV design and infrastructure investment. Doing so will move the field closer to equitable, safe AV deployment in the very places that stand to benefit most from improved mobility.

REFERENCES

Carsten, O., & Martens, M. H. (2019). How can humans understand their automated cars? HMI principles, problems and solutions. Cognition, Technology & Work, 21(1), 3–20. https://doi.org/10.1007/s10111-018-0484-0

Huang, G., & Pitts, B. J. (2020). The effects of engagement in physical exercise on semi-autonomous takeover request perception between younger and older adults. In Proceedings of the 64th Annual Meeting of the Human Factors and Ergonomics Society (p. 27). Human Factors and Ergonomics Society. https://par.nsf.gov/servlets/purl/10282753

Huang, G., Steele, C., Zhang, X., & Pitts, B. J. (2019). Multimodal cue combinations: A possible approach to designing in-vehicle takeover requests for semi-autonomous driving. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 63*(1), 1739–1743. https://doi.org/10.1177/1071181319631053

KPMG International. (2018). Autonomous vehicles readiness index. KPMG. https://assets.kpmg.com/content/dam/kpmg/xx/pdf/2018/01/avri.pdf

Market.us News. (2025, January 13). Autonomous vehicles statistics and facts. Market.us. https://www.news.market.us/autonomous-vehicles-statistics/

National Highway Traffic Safety Administration. (2022). Summary report: Standing general order on crash reporting for automated driving systems (Report No. DOT HS 813 324). U.S. Department of Transportation. https://www.nhtsa.gov/sites/nhtsa.gov/files/2022-06/ADS-SGO-Report-June-2022.pdf

SAE International. (2021). Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles (SAE Standard J3016_202104). SAE International. https://doi.org/10.4271/J3016_202104

United Nations Economic Commission for Europe. (n.d.). Automated driving. UNECE. Retrieved November 26, 2025, from https://unece.org/transport/road-transport/automated-driving

World Bank. (2024, March 21). From gridlock to green transport: Supporting electric mobility to meet the demand for passenger transport. World Bank. https://projects.worldbank.org/en/results/2024/03/21/from-gridlock-to-green-transport-supporting-electric-mobility-to-meet-the-demand-for-passenger-transport