Real Roads, Real Attitudes: Preliminary Longitudinal In-Field Findings of Autonomous Driving from Driver and Passenger Perspectives

Marvin Schittko
Institute of Psychology and Ergonomics, Cognitive Psychology and Cognitive Ergonomics
Technische Universität Berlin
Berlin, Germany
schittko@campus.tu-berlin.de

Abstract

Autonomous driving acceptance research is characterized by hypothetical scenarios, user perspectives distinguishing drivers from passengers, a behavior intention gap and the impact of time on measurements. Traditional acceptance models focus on system design characteristics, yet real-world adoption depends on broader attitudinal evaluations, how users appraise a technology's overall role and consequences. Usage Perception (UP) addresses this gap by capturing holistic judgments about technology usage and impact beyond system design. This contribution shows preliminary findings from a longitudinal in-field study that examines whether UP can account for real driving behavior across user perspectives and time. Eighty-two participants accumulated 164 hours on German autobahns with Society of Automotive Engineers Level 2+ automation, occupying both driver and passenger seats across two sessions in two measurement waves. UP significantly anticipated both behavior intention and use across all conditions. UP remained consistent across perspectives and time, suggesting its potential value for field-based acceptance research in autonomous driving.

CCS Concepts

• **Human-centered computing** → Human computer interaction (HCI); Empirical studies in HCI.

Keywords

Autonomous Driving, In-Field Study, Longitudinal Research, Active and Passive Use

ACM Reference Format:
Marvin Schittko. 2026. Real Roads, Real Attitudes: Preliminary Longitudinal In-Field Findings of Autonomous Driving from Driver and Passenger Perspectives. In *Extended Abstracts of the 2026 CHI Conference on Human Factors in Computing Systems (CHI EA '26), April 13–17, 2026, Barcelona, Spain.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3772363.3798563

1 Introduction

Current acceptance research on autonomous driving technologies is facing several research challenges. Theoretically, dominant acceptance frameworks in HCI emphasize system design characteristics [1]. However, users of autonomous systems form attitudes extending beyond functional assessments. They evaluate whether automation belongs on public roads, whether relinquishing control feels appropriate, and what societal consequences widespread adoption entails [2, 3]. Overall, these broader appraisals influence real-world engagement yet remain underrepresented in HCI-related design-focused acceptance models [4–6].

Furthermore, in applied research, investigations predominantly employ simulator environments or questionnaire-based assessments of imagined scenarios [7, 8]. Real on-road experiments where individuals engage with functioning automation under everyday traffic conditions remain exceptionally rare [9, 10]. As automation increases, occupants transition between controlling the vehicle and observing as passengers, involving fundamentally different engagement [11]. In HCI research, active interaction entails direct control and performance-related demands, whereas passive observation involves reduced agency and system-guided experience [12, 13]. Higher automation corresponds with negative attitudes despite stable usability ratings [14]. Additionally, time enables behavioral adaptation while introducing overreliance risks, underscoring the need to conceptualize interaction as ongoing recalibration [15, 16]. Furthermore, surveys indicate growing willingness to adopt automation, yet actual activation remains selective and situational [17, 18]. This intention-behavior gap represents a persistent challenge in HCI research: behavioral intention explains only modest portions of observed use [19–21]. To address these research challenges, we integrate Usage Perception (UP), a summative and abstract attitudinal measurement, capturing users' holistic appraisal of a technology's usage and impact beyond mere interface characteristics [22]. We test whether UP maintains stability and predictive relevance under authentic driving conditions through a longitudinal in-field study with Society of Automotive Engineers (SAE) Level 2+ automation, examining real traffic behavior from both driver and passenger perspectives across repeated measurement occasions.

2 Layered Attitudes and Hypothesis

2.1 Attitudinal Dimensions in Technology Evaluation

Complex technologies elicit additional evaluative responses that transcend design characteristics [4]. Users form judgments about whether a technology should exist, who benefits from its deployment, what risks accompany widespread adoption, and how its presence reshapes social contexts. In autonomous driving, such

CHI EA '26, Barcelona, Spain

ACM ISBN 979-8-4007-2281-3/2026/04
https://doi.org/10.1145/3772363.3798563

appraisals manifest as concerns about relinquishing control, moral implications of algorithmic decisions, privacy considerations, and societal readiness for automation [2, 3]. These evaluations operate independently from interface quality; a system may function smoothly yet evoke skepticism about its broader role. This distinction reflects the layered nature of attitudes toward highly complex technology, specifically autonomous driving [6, 23]. One layer addresses design and interaction quality; another addresses deployment, consequences, and societal integration. Applied models in autonomous driving research predominantly capture the former while underrepresenting the latter [7, 24].

2.2 Usage Perception as an Anchor

Attitudinal constructs possess theoretical properties relevant to field-based acceptance research. Attitudes demonstrate temporal persistence through cognitive mechanisms stabilizing existing beliefs [25, 26]. Simultaneously, attitudes connect to behavior enactment; they influence motivation and effort individuals invest in translating intentions into action [27, 28]. This combination of stability and behavioral relevance positions attitudes as anchors for understanding acceptance across varying conditions.

UP operationalizes this higher-order attitudinal layer [22]. The construct captures users' summative cognitive appraisal of a technology's overall usage and impact, which remain conceptually distinct from interface assessments. UP reflects whether users endorse a specific and directed use of a technology in their lives and society, independent of interface intuitiveness or interaction pleasantness. Prior research established UP's psychometric properties and capacity to stabilize acceptance models [29]. But can UP explain autonomous driving interaction, in-field, over time, with real use data and across user perspectives?

2.3 Interaction Conditions in Autonomous Driving

2.3.1 User Perspective. User Perspective distinguishes active from passive interaction. As automation increases in autonomous driving, the user's role shifts from driver to passenger, dissolving traditional boundaries [11]. Drivers maintain supervisory responsibility and experience automation as agency extension. Passengers observe without control authority, experiencing automation as an external agent. Higher automation corresponds with negative attitudes and reduced perceived control, despite stable usability ratings [14]. In HCI research, active interaction involves heightened emotional involvement and performance-related demands, whereas passive interaction supports emotional regulation and development [12, 13].

2.3.2 Temporal Exposure. Temporal Exposure captures evaluation evolution through repeated interaction. Time functions as a structuring factor enabling behavioral adaptation while introducing overreliance risks in autonomous driving contexts [15, 16]. Initial encounters involve novelty and uncertainty; subsequent sessions permit familiarization and calibrated expectations.

2.3.3 Behavioral Engagement. Behavioral Engagement refers to actual system use. Acceptance research frequently measures intentions rather than behavior, yet considerable discrepancy exists between stated willingness and actual engagement. This intention-behavior gap represents a persistent challenge in HCI research [19–21].

2.4 Hypothesis

We hypothesize that UP demonstrates stability across repeated real-world exposure while maintaining predictive relevance for actual behavior. This is contextualized within a research model as visualized in Figure 1.

H1: UP remains a stable predictor of behavioral intention across repeated usage.

H2: UP positively predicts actual system use behavior.

H3: This holds for both active (driver) and passive (passenger) user perspectives.

3 METHOD

3.1 Study Design

We conducted a longitudinal in-field driving experiment across multiple locations in Germany, including Berlin, Munich, Stuttgart, and Düsseldorf. The study employed a within-subjects design with two measurement points separated by intervals ranging from 24 hours to seven days (median = 2.4 days). At each measurement point, participants experienced both active (driver) and passive (passenger) perspectives by completing a predefined driving route once behind the steering wheel and once in the front passenger seat. Perspective order was counterbalanced across participants. Each driving session lasted approximately 90 minutes with two participants per vehicle, switching roles after roughly 30 minutes. A trained researcher occupied the back seat throughout all drives to monitor procedures, ensure safety compliance, and document behavioral observations without intervening unless required for safety. This design yielded 164 total driving hours across 82 participants. Data, analysis scripts, and supplementary materials are available at [https://osf.io/gxykv/overview]. To examine the demographics of the sample, please refer to Appendix A.1.

3.2 Apparatus & Procedure

The vehicle was a Mercedes-Benz E-Class equipped with SAE Level 2+ advanced driver assistance, enabling continuous longitudinal and lateral control during highway driving. The system supported adaptive cruise control, active steering assist, automated acceleration and braking, and fully automated lane changes, autonomously initiating overtaking maneuvers when lane markings and sufficient space were detected. Navigation-based route guidance enabled anticipatory lane selection for highway transitions. The system operated up to 130 km/h with driver responsibility enforced via capacitive sensors requiring hands-on steering contact. All sessions followed a predefined Autobahn route. Before highway driving, participants familiarized themselves with the vehicle for one to two kilometers. In the first measurement round, participants received standardized instruction on system activation, deactivation, and functional boundaries, using the system at least twice before engaging freely. In the second round, no additional instruction was provided; participants decided independently when and how to use the automation.

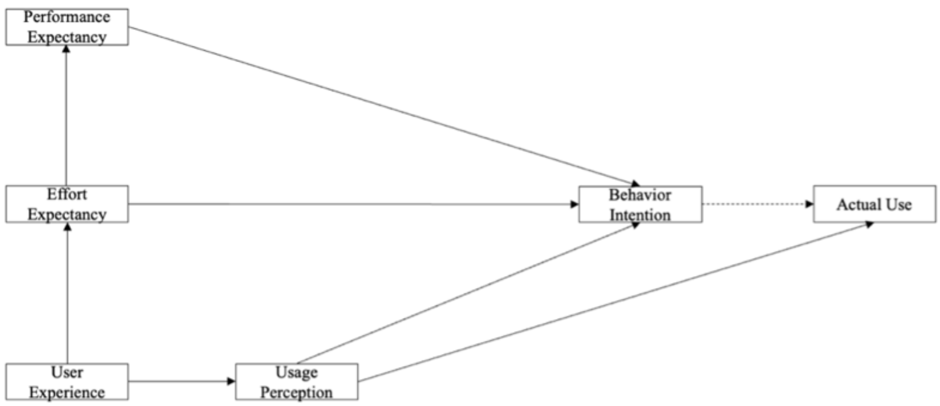

Figure 1: Research Model. Own presentation. The structural model was estimated separately across two measurement occasions (Time 1 and Time 2) and across two user-perspective groups (active vs. passive use). Dotted lines are not tested. The graphical model depicts the hypothesized structural relations only and is identical across groups and time points.

3.3 Measures

All questionnaire items were adapted from established scales using six-point response formats. Performance Expectancy ($\alpha = .888$) assessed perceived usefulness with four items [1]. Effort Expectancy ($\alpha = .905$) evaluated perceived ease of use with four items from the same source [1]. User Experience ($\alpha = .846$) was measured using twelve items reflecting affective experience components [30]. Usage Perception ($\alpha = .903$) was assessed through eight semantic differential items capturing cognitive representation of the technology [22]. Behavioral Intention ($\alpha = .890$) employed three items reflecting future usage plans [1].

Use was calculated from behavioral driving data representing aggregated actual system engagement. Three indicators captured distinct engagement dimensions: execution success (proportion of aborted relative to initiated autonomous actions), perceived safety (penalizing risk-driven human interventions), and usage intensity (proportion of initiated autonomous actions relative to all opportunities).

3.4 Analysis

Statistical analyses employed partial least squares structural equation modeling (PLS-SEM) in R, chosen for robustness under limited distributional assumptions appropriate for field-based data. Models specified participant random intercepts accounting for repeated measurements. Bootstrapping with 5,000 resamples generated confidence intervals for all path coefficients. H1 examined UP stability across time via multi-group analysis comparing measurement occasions; H2 tested direct paths from UP to actual Use; H3 analyses were conducted separately for active and passive user perspectives.

4 Results

Across all models, indicator loadings for core constructs were statistically significant ($\lambda \approx .63$–$.92$) with discriminant validity supported (HTMT $\approx .31$–$.85$). Use indicators showed lower loadings ($\lambda \approx .25$–$.49$) reflecting naturalistic behavioral variability. All structural paths within the technology acceptance model not explicitly examined in the hypotheses remained significant and stable across conditions. To examine full models, please refer to the Appendix A.2.

UP significantly predicted BI in the overall sample ($\beta = .32$, 95% CI [.19, .44]), remaining stable at Time 1 ($\beta = .31$, 95% CI [.14, .46]) and Time 2 ($\beta = .36$, 95% CI [.15, .56]). PLS multi-group analysis (5,000 bootstrap samples) revealed no significant between-occasion differences ($p = .645$). This stability held for active users at Time 1 ($\beta = .26$, 95% CI [.07, .44]) and Time 2 ($\beta = .33$, 95% CI [.07, .62]), and for passive users at Time 1 ($\beta = .33$, 95% CI [.06, .56]) and Time 2 ($\beta = .40$, 95% CI [.02, .66]). All remaining structural paths demonstrated comparable stability across time and perspectives. UP showed a significant direct effect on Use in the full sample ($\beta = .28$, 95% CI [.13, .54]), explaining 8% of variance ($R^2 = .08$) alongside 67% in BI ($R^2 = .67$). For active users, UP significantly predicted Use ($\beta = .37$, 95% CI [.16, 1.18]; $R^2 = .13$); for passive users, UP likewise predicted Use ($\beta = .27$, 95% CI [.10, .86]; $R^2 = .08$). These results provide preliminary support for H1, H2, and H3.

5 Discussion and Conclusion

5.1 Discussion

UP significantly predicted behavioral intention across both measurement occasions, demonstrating temporal stability. This finding aligns with theoretical accounts characterizing attitudes as hybrid psychological structures that balance persistence with adaptability through cognitive mechanisms stabilizing existing beliefs [25, 26].

This stability persisted for both active and passive user perspectives, indicating that holistic attitudinal appraisals transcend the positional differences in control and engagement [11, 14]. UP significantly predicted actual system use across all conditions, providing initial evidence for its capacity to bridge the intention-behavior gap. This pattern supports theoretical propositions that attitudes influence the motivation and effort individuals invest in translating intentions into action [27, 28]. The pattern held across user perspectives, though with notable differences. Active users showed stronger UP-to-Use relationships (β = .37) compared to passive users (β = .27), suggesting that holistic attitudes translate more directly into behavior when individuals exercise control over system engagement. This aligns with research indicating that active interaction involves heightened emotional involvement and direct agency [12]. Passive users demonstrated slightly stronger UP-to-BI relationships (β = .40 at Time 2), consistent with findings that passive interaction supports attitudinal development and emotional regulation [13].

5.2 Theoretical & Practical Implications

The stability of UP across repeated exposure and user perspectives positions it as a potential construct for overcoming central challenges in autonomous driving acceptance research. For practitioners, influencing overall perceptions of system deployment and societal impact may prove more consequential than optimizing isolated design features; communication strategies and public discourse shaping how users perceive autonomous driving's broader role may substantially influence adoption beyond interface improvements.

5.3 Limitations & Future Directions

The field-based design incorporated ecological noise inherent to authentic driving conditions. Behavioral Use indicators exhibited higher variability than attitudinal constructs, reflecting naturalistic data heterogeneity rather than measurement deficiency. The self-selective participant pool, predominantly technology-interested individuals positive toward autonomous driving, potentially limits generalizability to skeptical populations. The temporal interval (24 hours to 7 days) captures short-term stability; longer designs spanning months would clarify UP's extended predictive relevance. Finally, the SAE Level 2+ system required continuous driver supervision; generalizability to higher automation levels involving complete control transfer remains untested. A future paper building on this work in progress should engage more deeply with HCI literature, particularly in terms of contextualization and theoretical implications of the preliminary empirical evidence presented.

5.4 Author Declaration

The author thanks MBition GmbH for providing the test vehicle used in this study. The author is secondary affiliated with the Stuttgart University of Applied Science, Department of Business Psychology, Technology Acceptance Lab, which supported this research. The study was reviewed by the Ethics Committee of the University of Applied Science Stuttgart, which granted an official waiver of ethical approval. AI-based tools were used selectively to support editing. Full responsibility for the scientific integrity, originality, and content rests solely with the author.

5.5 Conclusion

These findings present preliminary empirical evidence from in-field autonomous driving contexts. Across 164 hours of real highway driving, findings suggest UP is a stable attitudinal anchor that reliably anticipated both future use intentions and observed system engagement. These patterns persisted whether participants controlled the vehicle or observed from the passenger seat, and across repeated exposure. The findings underscore UP as a practically valuable construct for field-based acceptance research, demonstrating that users' holistic appraisals of technology deployment advance understanding of autonomous driving adoption beyond design-focused metrics and intention-based predictions, providing a possible solution for persistent research challenges.

References

[1] Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. 2003. User acceptance of information technology: Toward a unified view. MIS Quarterly 27, 3, 425–478. https://doi.org/10.2307/30036540

[2] Silvestri, F., De Fabiis, F., and Coppola, P. 2024. Consumers' expectations and attitudes towards owning, sharing, and riding autonomous vehicles. Case Studies on Transport Policy 15, 101112. https://doi.org/10.1016/j.cstp.2023.101112

[3] Hőgye-Nagy, Á., Kovács, G., and Kurucz, G. 2023. Acceptance of self-driving cars among the university community: Effects of gender, previous experience, technology adoption propensity, and attitudes toward autonomous vehicles. Transportation Research Part F: Traffic Psychology and Behaviour 94, 353–361. https://doi.org/10.1016/j.trf.2023.03.005

[4] Brougham, D. and Haar, J. 2017. Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. Journal of Management & Organization 24, 2, 239–257. https://doi.org/10.1017/jmo.2016.55

[5] Cubric, M. 2020. Drivers, barriers and social considerations for AI adoption in business and management: A tertiary study. Technology in Society 62, 101257. https://doi.org/10.1016/j.techsoc.2020.101257

[6] Li, B., Chen, Y., Liu, L., and Zheng, B. 2023. Users' intention to adopt artificial intelligence-based chatbot: A meta-analysis. The Service Industries Journal 43, 15–16, 1117–1139. https://doi.org/10.1080/02642069.2023.2217756

[7] Koteczki, R. and Balassa, B. E. 2025. Systematic literature review of user acceptance factors of advanced driver assistance systems across different social groups. Transportation Research Interdisciplinary Perspectives 31, 101486. https://doi.org/10.1016/j.trip.2025.101486

[8] Zhang, T., Zeng, W., Zhang, Y., Tao, D., Li, G., and Qu, X. 2021. What drives people to use automated vehicles? A meta-analytic review. Accident Analysis & Prevention 159, 106270. https://doi.org/10.1016/j.aap.2021.106270

[9] Suryana, L. E., Nordhoff, S., Calvert, S. C., Zgonnikov, A., and Van Arem, B. 2024. A meaningful human control perspective on user perception of partially automated driving systems: A case study of Tesla users. In Proceedings of the 2024 IEEE Intelligent Vehicles Symposium (IV). IEEE, 409–416. https://doi.org/10.1109/iv55156.2024.10588431

[10] Lundgren, B. 2022. A new standard for accident simulations for self-driving vehicles: Can we use Waymo's results from accident simulations? AI & Society 39, 2, 669–673. https://doi.org/10.1007/s00146-022-01495-y

[11] Ive, H. P., Sirkin, D., Miller, D., Li, J., and Ju, W. 2015. "Don't make me turn this seat around!" In Adjunct Proceedings of the 7th International Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI '15). ACM, 50–55. https://doi.org/10.1145/2809730.2809752

[12] Poushneh, A. and Vasquez-Parraga, A. 2024. The effect of semiautonomous augmented reality on customer experience and augmentation experience. European Journal of Marketing 58, 8, 1910–1940. https://doi.org/10.1108/ejm-05-2022-0402

[13] Alsyouf, A., Lutfi, A., Alsubahi, N., Alhazmi, F. N., Al-Mugheed, K., Anshasi, R. J., Alharbi, N. I., and Albugami, M. 2023. The use of a technology acceptance model (TAM) to predict patients' usage of a personal health record system: The role of security, privacy, and usability. International Journal of Environmental Research and Public Health 20, 2, 1347. https://doi.org/10.3390/ijerph20021347

[14] Rödel, C., Stadler, S., Meschtscherjakov, A., and Tscheligi, M. 2014. Towards autonomous cars. In Proceedings of the 6th International Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI '14). ACM, 1–8. https://doi.org/10.1145/2667317.2667330

[15] Large, D. R., Burnett, G., Salanitri, D., Lawson, A., and Box, E. 2019. A longitudinal simulator study to explore drivers' behaviour in Level 3 automated vehicles. In Proceedings of the 11th International Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI '19). ACM, 222–232. https://doi.org/10.1145/3342197.3344519
[16] Kyriakidis, M., de Winter, J. C. F., Stanton, N., Bellet, T., van Arem, B., Brookhuis, K., and Happee, R. 2017. A human factors perspective on automated driving. Theoretical Issues in Ergonomics Science 20, 3, 223–249. https://doi.org/10.1080/1463922x.2017.1293187
[17] Picone, M., Errichiello, A., and Cartenì, A. 2023. How often are ADAS used? Results of a car drivers' survey. WSEAS Transactions on Systems 22, 566–577. https://doi.org/10.37394/23202.2023.22.57
[18] Carboni, A., Deflorio, F., Cossu, F., and Scotto, F. C. 2025. Observing user perception and usage of ADAS from a survey in Italy. Transportation Research Procedia 90, 647–654. https://doi.org/10.1016/j.trpro.2025.06.096
[19] Wu, J. and Du, H. 2012. Toward a better understanding of behavioral intention and system usage constructs. European Journal of Information Systems 21, 6, 680–698. https://doi.org/10.1057/ejis.2012.15
[20] Scherer, R., Siddiq, F., and Tondeur, J. 2019. The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. Computers & Education 128, 13–35. https://doi.org/10.1016/j.compedu.2018.09.009
[21] Sheeran, P. and Webb, T. L. 2016. The intention–behavior gap. Social and Personality Psychology Compass 10, 9, 503–518. https://doi.org/10.1111/spc3.12265
[22] Schittko, M., Mara, M., and Stiglbauer, B. 2025. Reintegrating human attitudes in the acceptance of AI-driven technology in HR across diverse user interactions. International Journal of Human–Computer Interaction, 1–13. https://doi.org/10.1080/10447318.2025.2549076
[23] Kaye, S.-A., Somoray, K., Rodwell, D., and Lewis, I. 2021. Users' acceptance of private automated vehicles: A systematic review and meta-analysis. Journal of Safety Research 79, 352–367. *Journal of Safety Research, 79*, 352–367. https://doi.org/10.1016/j.jsr.2021.10.002
[24] Damsara, K. and de Barros, A. 2025. A systematic review on user acceptance of advanced driver assistance systems (ADAS). Transportation Research Procedia 82, 3472–3482. https://doi.org/10.1016/j.trpro.2024.12.082
[25] Hart, W., Albarracín, D., Eagly, A. H., Brechan, I., Lindberg, M. J., and Merrill, L. 2009. Feeling validated versus being correct: A meta-analysis of selective exposure to information. Psychological Bulletin 135, 4, 555–588. https://doi.org/10.1037/a0015701
[26] Albarracín, D. and Shavitt, S. 2018. Attitudes and attitude change. Annual Review of Psychology 69, 1, 299–327. https://doi.org/10.1146/annurev-psych-122216-011911
[27] Mattson, T., Aurigemma, S., and Ren, J. 2023. Close the intention–behavior gap via attitudes: Case study of the volitional adoption of a two-factor authentication service. In Proceedings of the 56th Hawaii International Conference on System Sciences (HICSS '23). HICSS. https://doi.org/10.24251/hicss.2023.504
[28] Bhattacherjee, A. and Sanford, C. 2009. The intention–behaviour gap in technology usage: The moderating role of attitude strength. Behaviour & Information Technology 28, 4, 389–401. https://doi.org/10.1080/01449290802121230
[29] Schittko, M., Planing, P., and Müller, P. 2026. Stability through human perception: Technology acceptance models' robustness across various interaction perspectives and comparable technologies. Computers in Human Behavior Reports 21, 100930. https://doi.org/10.1016/j.chbr.2026.100930
[30] Buck, R., Khan, M., Fagan, M., and Coman, E. 2017. The User Affective Experience Scale: A measure of emotions anticipated in response to pop-up computer warnings. International Journal of Human–Computer Interaction 34, 1, 25–34. https://doi.org/10.1080/10447318.2017.1314612

A APPENDICES

A.1 Demographic Sample

Eighty-two individuals participated through local recruitment channels and university networks across all four locations. The sample represented demographic diversity across age, gender, education, employment, and income. Participants ranged from 19 to 70 years with a mean age of 32 years, predominantly young adults. Gender distribution included 65.9% female and 34.1% male participants. Educational attainment varied broadly: 29.3% held general higher education entrance qualifications, 26.8% bachelor's degrees, 20.7% master's degrees, and 17.1% completed vocational training. Regarding employment, 64.6% were employed and 28.0% were students. Monthly net income reflected diverse economic backgrounds, with 35.4% earning under € 1,000 and distributions extending above € 10,000. All participants provided informed consent. The study adhered to German Road Traffic Regulations. Participants received information about applicable rules, responsibilities, and insurance coverage at least two weeks before participation.

A.2 Statistical Models Results

Table 1: Full Statistical Models Across Conditions

Path	Full Sample	Time 1	Time 2	Passive	Active
UP → BI	.32	.31	.36	.29	.34
	[.19, .44]	[.14, .46]	[.15, .56]	[.13, .44]	[.14, .52]
UP → Use	.28	.23	.54	.27	.37
	[.14, .53]	[.06, 1.01]	[.26, 1.73]	[.10, .80]	[.15, 1.15]
PU → BI	.57	.60	.53	.62	.54
	[.45, .69]	[.46, .75]	[.31, .73]	[.46, .77]	[.36, .73]
PEU → PU	.39	.34	.47	.44	.36
	[.27, .51]	[.17, .50]	[.31, .63]	[.27, .60]	[.20, .53]
UX → UP	.85	.86	.85	.83	.88
	[.80, .90]	[.79, .92]	[.77, .93]	[.75, .90]	[.81, .95]
UX → PEU	.53	.59	.43	.58	.48
	[.43, .63]	[.46, .71]	[.27, .60]	[.44, .71]	[.34, .63]
R^2 BI	.67	.68	.67	.70	.63
R^2 PU	.15	.11	.22	.19	.13
R^2 PEU	.28	.35	.18	.33	.23
R^2 UP	.73	.74	.73	.68	.78
R^2 Use	.08	.05	.30	.08	.13

Values are standardized path coefficients (β) with 95% bootstrapped confidence intervals in brackets. BI = Behavioral Intention; UP = Usage Perception; PU = Perceived Usefulness; PEU = Perceived Ease of Use; UX = User Experience. R^2 values denote explained variance of endogenous constructs.