Influencing Factors of Trust in Automated Driving and Cultural Moderation Effects: Evidence from a Meta-Analysis[*]

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Abstract

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Full Text

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Practical Implications

The meta-analysis shows that traffic density has the strongest correlation with trust in automated driving, suggesting that system design should focus in particular on the complex traffic contexts in which vehicles operate. In addition, for different cultural markets, localized functional configurations can be implemented according to differences in users' concerns, so as to enhance levels of trust.

Abstract

To clarify the factors influencing trust in automated driving, this study conducted a meta-analysis of 134 included studies and identified 16 factors that have significant effects on trust in automated driving across four dimensions: personal traits, subjective perceptions, technological characteristics, and the traffic environment. The results show that attitudes toward automated driving, social influence, perceived benefits, perceived safety, system transparency, and traffic density are strongly associated with trust in automated driving. Cultural background plays a moderating role in some pathways. This study constructs a theoretical framework for trust in automated driving and provides theoretical and practical support for the cross-cultural adaptation of automated driving systems and the design of human-machine interaction.

Keywords trust in automated driving; influencing factors; meta-analysis; moderating effect

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Influencing Factors of Trust in Autonomous Driving and the Moderating Effect of Culture: Evidence Based on Meta-Analysis

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Abstract

With the rapid development of autonomous driving technology, research on the factors influencing trust in autonomous driving has increased. However, due to differences in sample data and social contexts, there are inconsistencies in the direction and strength of these factors' effects on trust. Therefore, this study aims to identify the key factors that influence trust in autonomous driving, standardize their effects, and explore the moderating role of cultural context. This will lead to the creation of an analytical framework that balances theoretical insight with practical relevance.

Meta-analysis is a research method that statistically re-examines existing empirical findings. In this study, a literature search and screening were first conducted, including 134 studies in the meta-analysis. Next, data coding and extraction were performed, analyzing 265 effect sizes. The 20 influencing factors were then categorized into four dimensions: "individual characteristics, subjective perceptions, technical features, and traffic environment." Additionally, the study assessed publication bias using the Inverse Safety Coefficient, Egger's regression coefficient, and Begg's test. Heterogeneity was analyzed with the Q-test and I^2 test. Finally, main effect tests were conducted, and subgroup analysis was used to explore moderating effects.

The research results indicate that 16 factors are significantly associated with trust in autonomous driving, distributed across the four dimensions mentioned above. Among these, the traffic environment dimension exhibits the strongest correlation with trust in autonomous driving. Specifically, factors such as attitude toward autonomous driving, social influence, perceived benefits, perceived safety, system transparency, and traffic density show a strong positive

correlation with trust. In contrast, factors including perceived risk, perceived ease of use, perceived usefulness, humanization, reliability, explainability, and automation level exhibit moderate correlations with trust. However, the correlations with driving experience, gender, and education level are relatively weak. Furthermore, cultural background plays a critical role in moderating these relationships, especially in the moderation of the relationship between gender, perceived risk, perceived ease of use, and trust in autonomous driving.

Through a comprehensive meta-analysis, we developed an integrated analytical framework for understanding trust in autonomous driving, which encompasses four critical dimensions: individual characteristics, subjective perceptions, technical features, and traffic environment. The framework establishes a systematic theoretical foundation for exploring the mechanisms underlying the formation of trust in autonomous driving. In addition, we identified and clarified the hierarchical relationships of effect strengths across these dimensions and key variables, a finding that provides guidance for prioritizing technological optimizations and formulating targeted promotion strategies. Furthermore, the examination of the moderating effect of cultural context elucidates the variability observed in prior research, offering a theoretical rationale for implementing differentiated promotion strategies tailored to diverse cultural contexts. Lastly, a thorough review of the existing literature highlights a predominant focus on mediating variables, such as personal self-perception, with numerous studies investigating their mediating roles within the "external stimulus—personal self-perception—trust in autonomous driving" logical framework.

This study provides valuable insights that can guide the research and development direction of autonomous vehicle manufacturers. It emphasizes the importance of enhancing the functional design of transparency and anthropomorphic features within autonomous driving systems. Furthermore, it advocates for the integration of design considerations that address the variability of traffic environments, as well as the diverse user priorities shaped by different cultural contexts, in order to foster greater user trust and facilitate the widespread adoption of the technology.

Key words: trust in autonomous driving, influencing factors, meta-analysis, moderating effects

1 Introduction

With the deep integration of 5G communications, artificial intelligence, and big-data technologies, automated driving (Automated Vehicle, AV) is becoming a typical paradigm of the Fourth Industrial Revolution and plays an important role in alleviating traffic congestion and improving road safety (Koppel et al., 2024). At present, automated driving systems are in a transitional stage from L2 (partial automation) toward L3 (conditional automation). The driver' s role is shifting from the absolute operator to the supervisor, and whether the driver can trust the automated driving system and cede control has become a core issue in the process of human–vehicle interaction (Frison et al., 2019; Qi Yue et al., 2024). Clarifying the main factors influencing trust in automated driving is not only an urgent requirement for deepening theories of human-machine interaction and understanding the mechanisms of user behavior, but also a practical need for optimizing automated driving system design, improving technology acceptance, and ensuring road-traffic safety and stability.

In automated-driving contexts, trust is defined as the attitude whereby, under uncertain and vulnerable circumstances, an individual believes that an agent can help them achieve a certain goal (Lee & See, 2004). Here, the automated driving system is the trustee, while the trustor encompasses different road users such as drivers, passengers, and pedestrians. Although the academic community has identified numerous antecedent variables of automated-driving trust, most previous reviews have directly drawn on theoretical frameworks from the human–automation trust loop (Hu et al., 2023), neglecting the characteristics that distinguish automated driving from automation trust in terms of safety risks, environmental complexity, and human–machine collaboration. At the same time, under the influence of sample data and differences in social context, the effects of the same factors on automated-driving trust show a high degree of heterogeneity. For example, some studies have found perceived usefulness to have a significant positive effect on automated-driving trust (Koppel et al., 2024; Man et al., 2025), whereas other studies have argued that the two are not directly related (Ramjan & Sangkaew, 2022). In terms of individual characteristics, some scholars have found that people with higher innovativeness are more inclined to trust automated driving systems (Nordhoff & Lehtonen, 2025), but empirical analyses have also shown that this variable has no significant effect on trust or even has a negative correlation (Li et al., 2020). In addition, the relationship between system reliability and automated-driving trust likewise diverges between positive correlation (Forster et al., 2018) and no necessary association (Taylor et al., 2023). These contradictions not only constrain the development of automated-driving trust theory, but also introduce uncertainty into interaction design, and thus require further quantification and clarification. Although meta-analyses have already examined factors influencing automated-driving trust, they have not specifically quantified the effect sizes and directions of the various factors. Moreover, research findings in this field have proliferated in recent years, while the literature included in existing meta-analyses is insufficiently up to date, making it difficult to reflect the current research frontier (Vongvit et al., 2022; Zhang et al., 2023). Therefore, this study intends to use a more refined meta-analysis to reveal the effects of different factors on automated-driving trust.

At the same time, cultural background may be an important source of heterogeneity. According to the 2024 global public survey report on artificial intelligence (GPO-AI), public trust in automated driving differs significantly across countries. Some 55% of Chinese respondents reported high trust in automated vehicles, whereas only 14% of respondents in the United Kingdom held a trusting attitude, and more than half (52%) expressed complete distrust. This indicates that cultural background may play an important role in the formation of trust in automated driving. Studies have pointed out that cultural values affect individuals' risk perceptions and willingness to accept emerging technologies (Hofstede et al., 2010; Hwang et al., 2024), providing a possible explanatory pathway for understanding the above differences. It is therefore necessary to incorporate cultural factors into the research framework of automated-driving trust.

In view of this, the present study adopts meta-analysis to systematically integrate and quantitatively analyze existing studies, with the aim of identifying the key influencing factors of automated-driving trust and revealing the potential moderating mechanisms of cultural background, thereby constructing an analytical framework with both theoretical generalizability and practical guidance.

2 Research Methods[1]

This study was written in accordance with the PRISMA guidelines.

2.1 Literature Retrieval and Screening

This study used two approaches: database searching and reference-list tracing. In Chinese databases such as CNKI, VIP, and Wanfang, the terms "automated vehicle," "autonomous vehicle," "automated driving system," "intelligent driving," "intelligent vehicle," or "driverless driving" were combined with "trust." In English-language databases including Scopus, ACM, EBSCO, Science Direct, IEEE, Web of Science, Proquest, Wiley, and Taylor & Francis, the keywords "automated vehicle" or "autonomous vehicle" or "automated driving" or "autonomous driving" or "automated car" or "driverless vehicle" or "driverless car" or "self-driving vehicle" or "self-driving car" or "ADAS" were combined with "Trust." Articles whose titles, abstracts, or keywords contained the above terms were retrieved. At the same time, a backward snowballing strategy was used to trace the reference lists of relevant studies in order to supplement potentially missed literature. The literature search was conducted through April 8, 2026, and a total of 10,644 records were ultimately obtained.

To ensure that the included literature met the aims of the study, screening was conducted according to the following criteria:

(1) The study had to be an empirical study on factors influencing trust in automated driving.

[1] This study was preregistered on the https://os.psych.ac.cn/preregiste platform; the registration number is 202506.00014.

(2) The study had to contain sufficient statistical data to determine the effect size, including sample size and relevant statistics such as r, t, F, and χ^2.

(3) The participants had to be physically and mentally healthy general populations; studies using patient groups as samples were excluded.

(4) The same dataset was included only once. If the same research data were published simultaneously in a dissertation, journal article, or conference paper, only one publication was selected to avoid repeated calculation of effect sizes.

Ultimately, 134 studies were included in the meta-analysis, spanning 2012–2026. The literature inclusion process is shown in Figure 1.

Flowchart content

- Records retrieved by keyword search: $n = 10595$
  - Chinese databases (CNKI, Wanfang, and VIP): $n = 1614$
  - English databases (Scopus, ACM, EBSCO, Science Direct, IEEE, Web of Science, Proquest, Wiley, Taylor & Francis): $n = 8981$
- Records obtained through snowballing: $n = 49$

↓

- Records after removal of duplicates: $n = 6697$

→ Excluded after reading titles and abstracts:
- Unrelated to the research topic ($n = 6012$)
- Review articles ($n = 149$)
- Non-empirical studies ($n = 108$)
- Participants not a healthy population ($n = 10$)
- Not in Chinese or English ($n = 5$)

↓

- Records obtained after initial screening: $n = 413$

→ Further excluded after full-text reading:
- Unrelated to the research topic ($n = 110$)
- Statistical quantities could not be extracted ($n = 57$)
- Full text not found ($n = 7$)
- Duplicate Chinese and English publications ($n = 1$)

↓

- Records obtained after secondary screening: $n = 238$

→ Excluded:
- Factors involved in fewer than 5 studies ($n = 104$)

↓

- Studies included in the meta-analysis: $n = 134$

Figure 1. Literature retrieval and screening process

2.2 Literature Coding

The first author, year of publication, cultural background, sample size, correlation coefficient—or statistics that could be converted—and the specific influenc
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Influencing factors were coded. When extracting influencing factors, variables with similar meanings were combined under a common name. Effect sizes were extracted with the independent sample as the unit; if the same publication contained multiple independent samples, they were coded separately. To ensure the accuracy of the coded information, coding was conducted independently by two people; when disagreements arose, consensus was reached by tracing back to the original literature and through group discussion.

Pearson' s correlation coefficient r was selected as the effect-size index. If the original study did not report a correlation coefficient, statistics such as t, F, χ^2, and β were converted according to the following formulas:

$$r = \sqrt{\frac{t^2}{t^2 + df}}; \qquad r = \sqrt{\frac{F}{F + df_e}}; \qquad r = \sqrt{\frac{\chi^2}{\chi^2 + N}};$$

$$r = \beta + 0.05\ (\beta \geq 0); \qquad r = \beta\ (\beta < 0) \quad (\beta \in (-0.5, 0.5))$$

(Card, 2012). In addition, cultural individualism scores were obtained from Hofstede Insights. Countries with individualism scores of 50 or above were classified as individualistic countries, whereas those below 50 were classified as collectivistic countries (Cheng et al., 2021; Zhang Lihua & Zhu He, 2021).

2.3 Screening of Influencing Factors

A total of 265 independent effect sizes and 91,792 samples were ultimately included. To ensure statistical power and precision, only variables that appeared at least 5 times were included (Jackson & Turner, 2017), and 20 influencing factors were finally selected for meta-analysis.

To clarify the logical attribution and mechanisms of action of each variable, the dimension of subjective perception was introduced on the basis of the three-dimensional "person-technology-environment" analytical framework (Hancock et al., 2011; Kaplan et al., 2021; Schaefer et al., 2016). Gao Zaifeng et al. (2021) pointed out that subjective perception is a core factor influencing users' trust in automated driving. In the process of interacting with automated driving systems, individuals do not respond directly to objective characteristics; rather, they need to cognitively process system characteristics (such as reliability and explainability) and contextual characteristics (such as task difficulty, road conditions, and weather conditions), transform external information into subjective perception, and then make trust judgments. In addition, in light of the particularity of automated driving application scenarios, environmental factors were defined as the traffic environment. In summary, the influencing factors were classified and integrated into four dimensions—personal traits, subjective perception, technological characteristics, and traffic environment. The specific categories and operational definitions of each variable are shown in Table 1.

Table 1 Influencing factors of trust in automated driving and their definitions

Influencing factors	Influencing factors	Variable description	References
Personal traits	Age	—	—
Personal traits	Gender	—	—
Personal traits	Personality	—	—
Personal traits	Educational level	—	—
Personal traits	Driving experience	The user' s years of driving conventional vehicles or level of driving-skill proficiency	(He Wenhao et al., 2024)
Personal traits	Trust propensity	A general tendency to place trust in others or in systems; a relatively stable internal personality characteristic of the individual	(Rotter, 1967)
Personal traits	Emotion	The emotional experience generated when the user uses an automated driving system	(Zieger et al., 2023)
Personal traits	Attitude toward AV	The user' s positive or negative evaluation of an automated driving system	(Yuen et al., 2020)

Influencing factors	Influencing factors	Variable description	References
Subjective perception	Social influence	The user' s subjective evaluation of the influence of important others, such as family members and friends, on their decision-making	(Liu et al., 2025)
Subjective perception	Perceived risk	The user' s subjective evaluation of potential negative consequences that automated vehicles may cause, such as safety accidents, privacy breaches, and system failures	(He et al., 2022)
	Perceived benefits	Users' subjective evaluation of the actual advantages and potential positive value brought by automated vehicles	(Nordhoff et al., 2023)
	Perceived usefulness	Users' subjective evaluation of whether automated vehicles can meet their daily travel needs	(Zhang et al., 2024)

	Perceived ease of use	Users' subjective evaluation of the difficulty of operating automated vehicles	(Zhang et al., 2024)
	Perceived safety	Users' subjective evaluation of the extent to which automated vehicles can protect themselves and others from injury or danger	(Sitinjak et al., 2024)
Technological characteristics	Reliability	The ability of an automated driving system to complete specified functions under specified conditions and within a specified time	(Zieger et al., 2023)
Technological characteristics	Explainability	The ability to explain to users the internal logic by which an automated driving system works or the reasons for making specific responses	(Rosenfeld & Richardson, 2019)
Technological characteristics	Anthropomorphism	Endowing the automated driving system with human-like traits, motivations, or emotions so that users can more easily understand and accept it	(Niu et al., 2018)

Technological characteristics	Transparency	The extent to which the operating state or decision-making process of an automated driving system is visible to users	(Seong & Bisantz, 2008)
Technological characteristics	Level of automation	The complexity of automated driving functions	(Miele et al., 2021)
Traffic environment	Traffic density	The number of vehicles per unit road length	(Jin et al., 2020)

3 Research Results

3.1 Publication Bias Test

The fail-safe number, Egger' s regression coefficient, and Begg test were used to assess publication bias. When the fail-safe number is less than $5k + 10$, or when the results of Egger regression and the Begg test are significant, this indicates a risk of publication bias. The results (Table 2) show that, although the fail-safe numbers for age and personality were relatively low, their Egger regression and Begg test results were both nonsignificant, indicating a relatively low risk of publication bias. The test indicators for all other influencing factors did not reach the level of significance.

Table 2 Publication Bias Test Results

Variable relationship	Variable relationship	k	N	Nfs	Egger' s test: regression intercept	Egger' s test: 95% CI	Begg test p value
Individual characteristics	Age	18	5240	43	0.66	[−1.55,2.87]	0.52
Individual characteristics	Gender	19	5492	101	0.99	[−0.72,2.71]	0.28

Variable relationship	Variable relationship	k	N	Nfs	Egger's test: regression intercept	Egger's test: 95% CI	Begg test p value
Individual characteristics	Personality	11	11155	2	0.34	[−1.32,2.00]	0.88
Individual characteristics	Attitude toward AV	8	3453	3533	−7.37	[−33.99,19.24]	0.80
Individual characteristics	Emotion	11	1960	109	0.81	[−6.38,8.01]	0.94
Individual characteristics	Education level	9	4211	293	3.31	[−12.78,19.40]	0.21
Individual characteristics	Trust propensity	7	1002	109	0.58	[−9.88,11.03]	0.65
Individual characteristics	Driving experience	15	2317	195	1.79	[−1.88,5.46]	0.88
Subjective perception	Social influence	8	12681	9400	−2.81	[−17.82,12.21]	0.32

Category	Variable relationship	k	N	Nfs	Effect size	95% CI	p
	Perceived risk	35	12910	7362	−1.80	[−6.97,3.38]	0.36

Category	Variable relationship	k	N	Nfs	Effect size	95% CI	p
	Perceived benefits	5	2128	1442	8.00	[−23.26,39.26]	0.62
	Perceived usefulness	18	7769	333	−9.67	[−22.34,3.00]	0.31
	Perceived ease of use	19	7995	5086	1.35	[−8.68,11.38]	0.60
	Perceived safety	5	1991	1062	−10.71	[−78.08,56.66]	0.62
Technical characteristics	Reliability	20	4815	4631	0.61	[−5.36,6.57]	0.16
Technical characteristics	Interpretability	11	1121	273	2.57	[−0.66,5.80]	0.35
Technical characteristics	Anthropomorphism	8	1128	305	2.85	[−8.71,14.41]	0.06
Technical characteristics	Transparency	21	3124	4472	−2.17	[−5.72,1.39]	0.25
Technical characteristics	Level of automation	9	596	144	0.77	[−0.56,2.11]	0.22
Traffic environment	Traffic density	8	704	189	−4.15	[−8.36,0.06]	0.08

Note: k is the number of studies included in the meta-analysis, N is the total sample size, and Nfs is the fail-safe coefficient. The same applies to the tables below.

3.2 Heterogeneity Test

Because the studies included in the meta-analysis differ in theoretical perspective, research context, and research methods, their findings may vary. Therefore, heterogeneity analysis was conducted using the Q test and the I^2 test. As shown in Table 3, the Q tests for all influencing factors were significant ($p < 0.05$). Except for the level of automation, for which $I^2 < 50\%$, all other variables showed significant heterogeneity. Therefore, a random-effects model was used to pool effect sizes.

Table 3 Heterogeneity Test Results

Category	Variable relationship	Q	$df\ (Q)$	p	I^2
Overall		18491.9	264	<0.001	98.57
Personal characteristics	Overall	2666.6	97	<0.001	96.36
Personal characteristics	Age	75.34	17	<0.001	77.43
Personal characteristics	Gender	62.27	18	<0.001	71.09
Personal characteristics	Personality	35.08	10	<0.001	71.50
Personal characteristics	Attitude toward AV	150.50	7	<0.001	95.35
Personal characteristics	Emotion	179.01	10	<0.001	94.42
Personal characteristics	Education level	266.15	8	<0.001	97.37
Personal characteristics	Trust propensity	151.60	6	<0.001	96.04
Personal characteristics	Driving experience	174.40	14	<0.001	91.97
Subjective perception	Overall	12104.31	89	<0.001	99.27

Category	Variable relationship	Q	$df\ (Q)$	p	I^2
Subjective perception	Social influence	754.75	7	<0.001	99.07
Subjective perception	Perceived risk	1354.65	34	<0.001	97.49
Subjective perception	Perceived benefits	15.78	4	<0.001	80.99

[[column heading not visible]]	[[column heading not visible]]	[[column heading not visible]]	[[column heading not visible]]	[[column heading not visible]]	[[column heading not visible]]
[[blank/merged cell not visible]]	Perceived usefulness	667.87	17	<0.001	97.46
[[blank/merged cell not visible]]	Perceived ease of use	439.21	18	<0.001	95.90
[[blank/merged cell not visible]]	Perceived safety	469.71	4	<0.001	99.15
Technical characteristics	Overall	1686.65	68	<0.001	95.97
Technical characteristics	Reliability	785.65	19	<0.001	97.58
Technical characteristics	Explainability	49.59	10	<0.001	79.83
Technical characteristics	Anthropomorphism	217.11	7	<0.001	96.78
Technical characteristics	Transparency	414.72	20	<0.001	95.18

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Technical characteristics	Level of automation	6.35	8	0.608	0.00
Traffic environment	Traffic density	72.89	7	<0.001	90.40

3.3 Main-Effect Tests and Effect-Size Analysis

According to Cohen' s (1988) criteria for judging effect sizes[2], except for age, personality, emotion, and trust propensity, the effect sizes of the remaining 16 influencing factors all reached the level of statistical significance (see Table 4).

Table 4 Summary of Effect Sizes for Factors Influencing Trust in Automated Driving

Variable relationship	Variable relationship	k	Overall effect size r	95% CI lower limit	95% CI upper limit	z value	p value
Overall	Overall	265	0.24	0.19	0.30	8.64	<0.001
Individual characteristics	Overall	98	0.20	0.14	0.25	6.41	<0.001
Individual characteristics	Age	18	0.06	−0.01	0.12	1.73	0.084
Individual characteristics	Gender	19	0.10	0.02	0.13	2.49	0.013
Individual characteristics	Personality	11	0.002	-0.07	0.08	0.05	0.963
Individual characteristics	Attitude toward AV	8	0.61	0.50	0.70	8.84	<0.001

Variable relationship	Variable relationship	k	Overall effect size r	95% CI lower limit	95% CI upper limit	z value	p value
Individual characteristics	Emotion	11	0.15	-0.05	0.34	1.50	0.133
Individual characteristics	Education level	9	0.20	0.00	0.37	2.00	0.046
Individual characteristics	Trust propensity	7	0.33	−0.02	0.61	1.86	0.063
Individual characteristics	Driving experience	15	0.24	0.08	0.39	2.97	<0.001
Subjective perception	Overall	90	0.20	0.09	0.30	3.60	<0.001
Subjective perception	Social influence	8	0.61	0.43	0.75	5.49	<0.001
Subjective perception	Perceived risk	35	−0.30	−0.40	−0.20	−5.44	<0.001
Subjective perception	Perceived benefits	5	0.60	0.53	0.67	12.02	<0.001
Subjective perception	Perceived usefulness	18	0.48	0.36	0.58	7.25	<0.001

[2] $|r| < 0.1$ indicates no correlation; $0.1 \leq |r| < 0.3$ indicates a weak correlation; $0.3 \leq |r| < 0.5$ indicates a moderate correlation; $|r| \geq 0.5$ indicates a strong correlation.

	Perceived ease of use	19	0.36	0.26	0.45	6.75	<0.001
	Perceived safety	5	0.55	0.12	0.80	2.45	0.014
Technical characteristics	Overall	69	0.45	0.36	0.52	9.37	<0.001
Technical characteristics	Reliability	20	0.35	0.28	0.42	9.03	<0.001
Technical characteristics	Explainability	11	0.35	0.21	0.47	4.82	<0.001
Technical characteristics	Anthropomorphism	8	0.42	0.09	0.67	2.43	0.015
Technical characteristics	Transparency	21	0.50	0.36	0.62	6.09	<0.001
Technical characteristics	Level of automation	9	0.35	0.28	0.42	8.66	<0.001
Traffic environment	Traffic density	8	−0.63	−0.82	−0.32	−3.55	<0.001

The results show that the four dimensions—personal characteristics, subjective cognition, technical characteristics, and traffic environment—all have significant positive correlations with trust in automated driving. Among them, traffic density is strongly correlated with trust in automated driving ($r = -0.63, p < 0.001$); the technical characteristics dimension is moderately correlated with trust in automated driving ($r = 0.45, p < 0.001$).

Within the personal-characteristics dimension, attitude toward AVs ($r = 0.61, p < 0.001$) is significantly positively correlated with trust in automated driving. Gender ($r = 0.10, p = 0.013$), education level ($r = 0.20, p = 0.046$), and driving experience ($r = 0.24, p < 0.001$) show significant but relatively weak correlations, whereas personality, age, emotion, and trust propensity show no significant correlations with trust in automated driving.

Within the subjective-cognition dimension, all factors are significantly correlated with trust in automated driving. Specifically, social influence ($r = 0.61, p < 0.001$), perceived benefit ($r = 0.60, p < 0.001$), and perceived safety ($r = 0.55, p = 0.014$) are strongly correlated with trust; perceived risk ($r = -0.30, p < 0.001$), perceived usefulness ($r = 0.48, p < 0.001$), and perceived ease of use ($r = 0.36, p < 0.001$) are moderately correlated with trust.

Within the technical-characteristics dimension, all subvariables are positively correlated with trust. Among them, transparency is strongly correlated with trust ($r = 0.50, p < 0.001$); reliability ($r = 0.35, p < 0.001$), explainability ($r = 0.35, p < 0.001$), anthropomorphism ($r = 0.42, p < 0.001$), and level of automation ($r = 0.35, p < 0.001$) all show moderate correlations.

3.4 Test of Moderating Effects

When subgroup analysis was used to test moderating effects, the number of effect sizes at each level should be no fewer than 3 (Zhan Juanjuan et al., 2023; Zhang Yali et al., 2021) . As shown in Table 5, cultural background has a significant moderating effect on the relationships between gender ($Q_B = 8.29, p = 0.004$), perceived risk ($Q_B = 4.27, p = 0.039$), and perceived ease of use ($Q_B = 5.13, p = 0.024$) with trust in automated driving.

Specifically, under an individualistic cultural background, the correlations of gender ($r = 0.18$) and perceived risk ($r = -0.58$) with trust in automated driving are significantly higher than those under a collectivistic cultural background ($r_{\text{gender}} = 0.02,\ r_{\text{perceived risk}} = -0.25$); whereas the correlation between perceived ease of use ($r = 0.12$) and trust in automated driving under an individualistic cultural background is significantly lower than that under a collectivistic cultural background ($r = 0.40$).

Because some variables included in the meta-analysis involved only individualism or collectivism, with a single category, no moderating-effect test was conducted.

Table 5. Analysis of the Moderating Effect of Cultural Background

Influencing Factor	Moderating Variable	k	r	95% CI Lower Limit	95% CI Upper Limit	Q_B	df	p
Gender	Individualism	8	0.18	0.09	0.28	8.29	1	0.004
Gender	Collectivism	11	0.02	−0.04	0.07	8.29	1	0.004
Education level	Individualism	3	0.15	−0.02	0.30	0.14	1	0.705

Influencing Factor	Moderating Variable	k	r	95% CI Lower Limit	95% CI Upper Limit	Q_B	df	p
Education level	Collectivism	6	0.21	−0.10	0.48	0.14	1	0.705
Driving experience	Individualism	5	0.17	0.05	0.27	0.85	1	0.356
Driving experience	Collectivism	10	0.29	0.05	0.49	0.85	1	0.356
Perceived risk	Individualism	7	−0.58	−0.77	−0.29	4.27	1	0.039
Perceived risk	Collectivism	28	−0.25	−0.36	−0.13	4.27	1	0.039
Perceived ease of use	Individualism	3	0.12	0.11	0.35	5.13	1	0.024
Perceived ease of use	Collectivism	16	0.40	0.31	0.49	5.13	1	0.024
Reliability	Individualism	12	0.40	0.28	0.51	0.88	1	0.349
Reliability	Collectivism	8	0.54	0.24	0.75	0.88	1	0.349
Explainability	Individualism	5	0.30	−0.023	0.57	0.04	1	0.838
Explainability	Collectivism	5	0.33	0.21	0.45	0.04	1	0.838
Anthropomorphism	Individualism	5	0.47	−0.085	0.80	0.61	1	0.437
Anthropomorphism	Collectivism	3	0.25	0.03	0.45	0.61	1	0.437
Transparency	Individualism	7	0.46	0.28	0.60	0.31	1	0.579
Transparency	Collectivism	14	0.52	0.34	0.66	0.31	1	0.579

4 Discussion

After excluding nonsignificant factors, this study systematically reviewed the influencing factors significantly associated with trust in autonomous driving from four dimensions: personal characteristics, subjective perception, technological characteristics, and the traffic environment (see Figure 2). The meta-analysis results show that, overall, the above four dimensions are significantly correlated with trust in autonomous driving, supporting the rationality of incorporating these four dimensions into the trust research model.

Figure 2. Influencing factors of trust in autonomous driving and effect sizes. The chart groups factors into personal characteristics, subjective perception, technical characteristics, and traffic environment. Personal characteristics: gender 0.10, attitude toward AV 0.61, education level 0.20, driving experience 0.24. Subjective perception: social influence 0.61, perceived risk −0.30, perceived benefits 0.60, perceived usefulness 0.48, perceived ease of use 0.36, perceived safety 0.55. Technical characteristics: reliability 0.35, interpretability 0.35, anthropomorphism 0.42, transparency 0.50, automation level 0.35. Traffic environment: traffic density −0.63.

Figure 1: Figure 2. Influencing factors of trust in autonomous driving and effect sizes. The chart groups factors into personal characteristics, subjective perception, technical characteristics, and traffic environment. Personal characteristics: gender 0.10, attitude toward AV 0.61, education level 0.20, driving experience 0.24. Subjective perception: social influence 0.61, perceived risk −0.30, perceived benefits 0.60, perceived usefulness 0.48, perceived ease of use 0.36, perceived safety 0.55. Technical characteristics: reliability 0.35, interpretability 0.35, anthropomorphism 0.42, transparency 0.50, automation level 0.35. Traffic environment: traffic density −0.63.

Figure 2 Influencing factors of trust in autonomous driving and effect sizes

4.1 Analysis of Influencing Factors in the Personal-Characteristics Dimension

The analysis of the personal-characteristics dimension shows that users' attitude toward AV has the strongest correlation with trust in autonomous driving, a result that confirms the core proposition of the theory of planned behavior. As an individual' s affective evaluation of a specific object (Yuen et al., 2020), attitude reflects users' positive or negative cognition of automated driving systems and is closely psychologically associated with the formation of trust; that is, a positive attitude is usually accompanied by a higher level of trust in autonomous driving.

In addition, driving experience shows a moderate positive correlation with trust in autonomous driving. This may be because experienced drivers have a deeper understanding of vehicle control and the traffic environment, and can more accurately grasp the capability boundaries and applicable scenarios of automated driving systems. At the same time, experienced drivers have often been exposed to driver-assistance systems, and these interaction experiences also lay a foundation for the establishment of trust in autonomous driving. By contrast, gender and education level show weaker correlations with trust in autonomous driving, indicating that demographic variables have relatively limited direct effects on trust.

Compared with technical characteristics and the traffic environment, the personal-characteristics dimension as a whole has a weaker relationship with trust in autonomous driving. Although many scholars emphasize the importance of individual heterogeneity in shaping trust in autonomous driving (Li et al., 2020; Liang et al., 2023; Nordhoff et al., 2023), and argue for the necessity of developing personalized automated driving systems, the results of this study do not fully support that view. The meta-analysis found that deeper personal characteristics such as age and personality are not significantly correlated with trust in autonomous driving, while demographic variables such as gender and education level also have weak relationships with trust in autonomous driving. Therefore, with respect to trust in autonomous driving, the driving role of the technology' s own characteristics is stronger than that of users' personal characteristics. Future R&D efforts should still focus on improving the technology rather than on configuring personalized functions. However, this does not deny the value of personal characteristics. Future research may further explore the interaction between personal characteristics and technical characteristics, so as to reveal their moderating effects and boundary conditions in specific situations or user groups.

It is noteworthy that the meta-analysis found no correlation between individuals' propensity to trust and trust in autonomous driving. This indicates that trust in autonomous driving is a dynamic, object-perception-based situational trust, and is less affected by users' own stable trait trust, reflecting its dependence on the situation and the object.

Color figure available in the online version.

4.2 Analysis of Influencing Factors in the Subjective Perception Dimension

The subjective perception dimension is significantly positively correlated with trust in autonomous driving, validating the effectiveness of incorporating subjective perception into the theoretical framework of trust in autonomous driving. Among these factors, social influence, perceived benefits, and perceived safety are strongly correlated with trust in autonomous driving, with social influence showing the strongest association. Social influence reflects the fact that, when individuals form trust judgments, they are readily shaped by the opinions of important others around them and by social norms (Liu et al., 2025). This is especially the case when facing an emerging technology such as autonomous driving: compared with rational evaluations of the system' s own value, users are more susceptible to the immediate influence of external evaluations and group norms.

In addition, perceived ease of use and perceived usefulness are moderately positively correlated with trust in autonomous driving and constitute core factors in the subjective perception dimension. This conclusion is highly consistent with the Technology Acceptance Model (TAM), indicating that when users have a stronger perception of the practicality and convenience of autonomous driving systems, they are often more likely to develop trust. Further, together with the strong correlations of perceived benefits and perceived safety with trust in autonomous driving, this verifies an important intrinsic link between the perceived value system users form toward autonomous driving and the formation of trust.

By contrast, perceived risk is significantly negatively correlated with trust in autonomous driving, exhibiting a certain negative constraining effect. However, the meta-analysis results show that the strength of this negative effect is relatively limited and weaker than the positive effects of perceived ease of use and usefulness. Overall, in the formation of trust in autonomous driving, the subjective perception dimension exhibits both positive driving effects and negative constraining effects, with positive drivers predominating.

4.3 Analysis of Influencing Factors in the Technological Characteristics Dimension

Except for the traffic environment, the technological characteristics dimension has the strongest correlation with trust in autonomous driving, indicating that the technology itself is the key driver of trust formation. Among these factors, transparency is the strongest factor within the technological characteristics dimension, suggesting that the transparency of autonomous driving systems is a core prerequisite for user trust. The "algorithmic black box" of autonomous driving systems often prevents users from predicting vehicle behavior and also makes it difficult for them to understand the deeper logic behind decisions (Siau & Wang, 2020). Such opacity readily triggers public concerns about the safety and reliability of autonomous driving, thereby reducing trust. By contrast, highly transparent autonomous driving systems allow users to grasp the vehicle's operating status clearly and in real time, reducing fear caused by the unknown and thereby enhancing trust.

In addition, system anthropomorphism is moderately positively correlated with trust in autonomous driving. Based on social-cognitive instincts, users tend to trust machines that possess human-like features in appearance, interactive voice, and behavior (Kaplan et al., 2021). By comparison, the effect sizes of reliability, explainability, and level of automation are similar and are all slightly lower than that of anthropomorphism. Among them, reliability is essentially users' cognition and recognition of the stability of technological capability; explainability is an extension of transparency, focusing on addressing the rationality of system decisions. Meanwhile, a higher level of automation means that the system can undertake more tasks and make decisions, thereby reducing human effort and further enhancing trust; however, this enhancement is constrained by users' cognition of the boundaries of technological capability (Hjälmdahl et al., 2017).

4.4 Analysis of Influencing Factors in the Traffic Environment Dimension

Among all included variables, traffic density has the strongest correlation with trust in autonomous driving. High-density traffic scenarios are typically accompanied by more frequent vehicle interactions, shorter takeover reaction times, more unpredictable behavior by other road users, and higher potential conflict risk. In this context, users perceive increased system uncertainty and risk, which in turn lowers their judgments of system reliability and suppresses trust. This result once again emphasizes the context-sensitive and dynamic nature of trust in autonomous driving.

Although limited by the relatively singular classification of traffic environments in the existing literature, which prevents the inclusion of more effective variables related to the traffic environment, this result nevertheless reveals, to a certain extent, the dynamicity and complexity of the external environment in the process of trust formation⋯

plays a key role in the burden. As the operating context of autonomous driving systems, the complexity of the traffic environment directly determines task difficulty and system performance. Users evaluate system capability by observing how the system responds in different environments, and adjust their trust judgments accordingly.

4.5 Analysis of Moderating Factors in Trust in Autonomous Driving

The analysis of moderating effects shows that cultural background significantly moderates the relationships between gender, perceived risk, and perceived ease of use, on the one hand, and trust in autonomous driving, on the other; however, its moderating effects on most technology-characteristic factors are not significant. This result suggests that cultural values do not uniformly affect all antecedents of trust, but instead selectively strengthen particular pathways that align with their own core logic.

Specifically, in individualistic cultures that emphasize personal agency and sense of control (Li et al., 2018), trust in autonomous driving exhibits stronger individually driven characteristics. On the one hand, the influence of gender on trust in autonomous driving is more pronounced in individualistic cultures. This stems from the emphasis placed by individualistic cultures on individual differences and uniqueness, allowing gender-based heterogeneity to be more fully manifested; by contrast, in collectivistic cultures, group norms and social consensus often dilute the influence of individual characteristics. On the other hand, the negative association between perceived risk and trust in autonomous driving is especially salient in individualistic cultures: the strong pursuit of individual autonomy makes users in such cultures more sensitive to potential risks and safety threats. By comparison, trust formation in collectivistic cultures depends more on the social adaptability of the technology and its acceptance by the group (Yun et al., 2021). Therefore, the positive effect of perceived ease of use is more prominent, because ease of use can lower the threshold for group adoption and promote social integration.

Through its deep value system, cultural background shapes different "lenses" through which users evaluate autonomous driving systems. Individualistic cultures tend to establish trust from the perspective of individual rights and risk control, whereas collectivistic cultures tend to establish trust from the perspective of the technology' s convenience for group collaboration. This finding clarifies the differences in the formation mechanisms of trust in autonomous driving across cultural backgrounds, and provides an important theoretical basis for system design and differentiated technology communication in a globalized context.

5 Conclusions and Prospects

5.1 Research Conclusions

Based on meta-analytic methods, this study systematically integrated and examined the influencing factors of trust in autonomous driving. The main findings are as follows:

(1) A four-dimensional integrated framework was constructed, covering personal characteristics, subjective perceptions, technological characteristics, and the traffic environment, thereby providing a systematic theoretical foundation for understanding the formation mechanisms of trust in autonomous driving.

(2) The effect strengths of each dimension and core variable were clarified. The study found that the traffic environment and technological characteristics are strongly associated with trust in autonomous driving. Among them, traffic density, attitude toward AV, social influence, perceived benefits, perceived safety, and system transparency are the core variables with the most significant associations.

(3) The moderating effect of cultural background was verified for the first time at the meta-analytic level, confirming that it significantly moderates the influence pathways of gender, perceived risk, and perceived ease of use on trust. This effectively explains the sources of heterogeneity in existing studies.

5.2 Research Prospects

Based on the meta-analytic results, future research can be further deepened in the following three directions:

(1) Expand research on traffic-environment contextual factors. Given that the variables currently incorporated into the traffic-environment dimension are relatively limited, future research should systematically examine the effects of multidimensional contextual variables such as road type and weather conditions on trust in autonomous driving, and test their relationship with its

interactions with other dimensions, so as to construct a more comprehensive contextualized model of trust.

(2) Exploration of variables that remain scarce in the literature. Owing to the statistical power requirements of meta-analysis, important variables such as driving style, ride comfort, and system predictability were not included in the tests. Future research should focus on these emerging antecedents and, through large-sample empirical studies, reveal their mechanisms of action, thereby further improving the theoretical system of trust in automated driving.

(3) Strengthening fine-grained analysis of moderating mechanisms. Because of limitations in the number of subgroups, this study was unable to fully examine moderating variables such as the measurement method for trust in automated driving and the experimental environment. Future research should adopt multidimensional and multi-scenario research designs for comparative studies, providing data support for theoretical refinement and practical precision.

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