The Impact of Privacy Risk Perception on Initial Trust in Autonomous Vehicles: Differential Responses Between Practitioners and Non-Practitioners

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Abstract

Previous research has primarily focused on the public' s insufficient trust in autonomous driving systems; however, excessive trust among ordinary consumers can also lead to system misuse, thereby increasing usage risks. This paper systematically explores the influence of professional background on initial trust through three studies, focusing on comparing and calibrating the trust levels of ordinary consumers to align them more closely with those of expert practitioners. Study 1 found that non-practitioners exhibit a tendency toward over-trust, and that an interaction effect exists between privacy risk perception and professional background on initial trust. Study 2, by manipulating privacy risk levels, found differential responses between practitioners and non-practitioners: increased risk levels significantly enhanced non-practitioners' privacy risk perception and reduced their initial trust, whereas practitioners' initial trust was less affected by risk variations. Study 3 further revealed non-practitioners' asymmetric response to privacy risk information: in low-risk scenarios, despite a significant increase in privacy risk perception, initial trust showed no significant change; whereas in high-risk scenarios, privacy risk perception increased significantly and initial trust decreased markedly. These results reveal the interaction between professional background and privacy risk perception on initial trust in autonomous driving, highlight differences between practitioners and non-practitioners in initial trust formation, and suggest that designers of autonomous driving systems should adopt more targeted trust calibration strategies to address the differential responses of practitioners and non-practitioners.

Full Text

The Impact of Privacy Risk Perception on Initial Trust in Autonomous Vehicles: Differential Responses of Professionals and Non-Professionals

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Abstract

Previous research has primarily focused on insufficient trust in autonomous driving systems, yet excessive trust among ordinary consumers may equally lead to system misuse and increased usage risks. This paper systematically explores the influence of professional background on initial trust through three studies, with a focus on comparing and calibrating the trust levels of ordinary consumers to align more closely with those of expert practitioners. Study 1 reveals that non-professionals exhibit a tendency toward over-trust, and that privacy risk perception and professional background interact to influence initial trust. Study 2 manipulates privacy risk levels and finds differential responses between professionals and non-professionals: elevated risk levels significantly enhance non-professionals' privacy risk perception and reduce their initial trust, whereas professionals' initial trust is less affected by risk variations. Study 3 further reveals non-professionals' asymmetric response to privacy risk information: under low-risk conditions, despite significantly increased privacy risk perception, initial trust shows no significant change; under high-risk conditions, privacy risk perception increases significantly and initial trust declines markedly. These results illuminate the interactive effect of professional background and privacy risk perception on initial trust in autonomous driving, highlight differences between professionals and non-professionals in initial trust formation, and suggest that autonomous system designers should adopt more targeted trust calibration strategies to address these differential responses.

Keywords: autonomous vehicles, initial trust, professional background, perceived privacy risk, human-AI trust
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With the rapid development of artificial intelligence technology, autonomous vehicles (AVs) have demonstrated clear advantages, offering users a more relaxed travel experience [?, ?, ?]. However, technological maturity is only a prerequisite for adoption; whether people trust autonomous driving systems is the key factor influencing their acceptance and use of the technology [?, ?, ?, ?]. In human-computer interaction, trust is defined as an individual' s expectation that an agent system can help achieve their goals under conditions of risk and uncertainty [?, ?, ?]. Insufficient trust leads to user rejection of technology [?, ?], while excessive trust may similarly cause safety hazards such as delayed takeover [?, ?, ?]. Therefore, enabling users to maintain appropriate trust has become a critical issue in the development of autonomous driving.

Currently, the public still harbors significant doubts about the safety and reliability of autonomous vehicles [?, ?, ?, ?, ?]. Consumer survey data from Deloitte China (2019) shows that over half of respondents adopt a cautious attitude toward autonomous driving technology, with more than 53% supporting stronger government regulation. A survey by PricewaterhouseCoopers (2023) further confirms this cautious stance, revealing that 60%–70% of respondents lack trust in autonomous vehicles. This widespread trust crisis not only hinders the commercialization of autonomous vehicles but also delays the arrival of fully autonomous driving [?, ?, ?]. Against this backdrop, previous research has primarily focused on insufficient trust [?, ?]. However, excessive user trust in autonomous driving also poses serious risks [?, ?]. If individuals overestimate system capabilities, they may overlook potential risks and fail to correct errors in a timely manner [?, ?].

Excessive trust refers to a situation where an individual' s subjective trust level exceeds the objective trustworthiness of the system. Previous studies have found that in emergency situations, individuals often struggle to accurately assess intelligent system capabilities and are more prone to over-trust [?, ?, ?]. Other research suggests that underestimating risks can also lead to excessive trust. Booth et al. (2017) placed a robot at a dormitory entrance and asked passersby to help it enter the dormitory. The results showed that even though students were aware that allowing the robot into the dormitory could pose security risks, they still permitted entry, reflecting over-trust in robots. In real life, excessive trust in autonomous driving systems could directly lead to catastrophic accidents.

Notably, trust does not manifest uniformly across all user groups. Existing research often treats autonomous vehicle users as a homogeneous group [?, ?, ?], but in reality, users include both industry professionals deeply engaged in the field and ordinary consumers lacking specialized knowledge [?, ?]. These two groups exhibit significant differences in knowledge reserves and trust mechanisms: autonomous driving professionals are more familiar with automated systems and can more rationally evaluate system performance and potential risks [?, ?, ?, ?], making their trust levels closer to the system' s actual trustworthiness. In contrast, non-professionals, due to limited relevant knowledge and evaluation capabilities, are more likely to form inappropriate trust levels.

More importantly, ignoring the background differences between professionals and ordinary consumers may result in product designs that fail to meet real user needs [?, ?, ?]. Surveys indicate clear divergences in needs between these groups: in the Chinese market, professionals prioritize autonomous vehicles' infotainment systems, while their emphasis on on-demand service features (67%) is significantly lower than that of ordinary consumers (94%) (PricewaterhouseCoopers, 2023). This supply-demand cognitive gap may not only reduce user satisfaction [?, ?, ?] but also further affect users' trust levels and acceptance, potentially even triggering safety risks in specific contexts. A typical case is the privacy risk issue: professionals often downplay data usage and secondary utilization boundaries in communication, leading non-professionals to over-trust privacy protection levels, while any information leakage incident triggers a sharp decline in trust [?, ?]. Therefore, comparing the trust mechanism differences between professionals (as designers) and non-professionals (as users) is key to understanding and calibrating trust levels and achieving user-centered, high-credibility design.

In summary, this study aims to explore how to make non-professionals' initial trust levels closer to those of professional designers, thereby forming more reasonable and moderate initial trust. Answering this question is crucial for enhancing the safety and efficiency of human-machine collaboration. Based on this, the study focuses on SAE Level 3 autonomous vehicles, systematically examines the influencing factors of initial trust, and compares differences in trust mechanisms between professionals and non-professionals to reveal differential responses in initial trust between these two groups.

1.1 Initial Trust in Autonomous Vehicles

Current theory agrees that trust in autonomous vehicles is a dynamic process [?, ?, ?]. Building on the dynamic trust model [?, ?] and the two-stage trust model [?, ?], Gao et al. (2021) proposed a dynamic trust framework that integrates trust development stages and influencing factors. This framework divides trust development into four stages: dispositional trust, initial trust, real-time trust, and post-hoc trust, with the latter three collectively termed historical trust states. During operator-system interaction, trust in the system gradually shifts from dispositional trust to being dominated by historical trust components [?, ?]. Among these, initial trust forms the foundation of this process [?, ?, ?]. Hoff and Bashir (2015) define initial trust as an individual's trust in an automated system based on existing knowledge in the absence of direct experience. Research shows that initial trust plays a crucial role in consumers' acceptance and purchase intentions regarding autonomous vehicles [?, ?, ?]. Therefore, initial trust is the core focus of this study.

1.2 Factors Influencing Initial Trust in Autonomous Vehicles

The dynamic trust framework categorizes trust influencing factors into three aspects: operator characteristics, system characteristics, and contextual characteristics [?, ?]. For autonomous vehicles, initial trust formation particularly depends on two types of operator factors: first, relatively stable inherent traits such as gender, age, and educational background, which are independent of the system and context and constitute individuals' basic trust propensity; second, prior experience accumulated through interaction with similar systems or social learning, where perceptions based on system and contextual features and social influence from others are important sources of prior experience.

Existing research has found that individuals' performance perception and risk perception of autonomous vehicles directly affect initial trust. For example, Zhang et al. (2019), based on the Technology Acceptance Model (TAM; Davis et al., 1989), found that perceived usefulness and safety risk perception are key factors influencing initial trust in autonomous vehicles. Additionally, social influence plays an important role [?, ?], as external information such as others' evaluations, advertising, and public opinion can change user attitudes [?, ?, ?]. For instance, Zhang et al. (2020) surveyed 647 Chinese drivers and found that social influence indirectly enhanced the intention to use autonomous vehicles through initial trust. These results collectively demonstrate the central role of system performance perception (e.g., perceived usefulness, perceived flaws), system safety perception (e.g., safety risk perception, privacy risk perception), and social influence in shaping initial trust in autonomous vehicles.

However, existing models still have limitations in explaining group differences and have not adequately considered the role of professional background [?, ?, ?, ?]. Professional background reflects individual differences in professional knowledge and experience accumulation, which may lead to different subjective perceptions and trust judgments when facing the same system [?, ?, ?]. For example, industry professionals are more likely to identify system flaws or privacy risks based on professional knowledge, thereby forming different initial trust levels from ordinary consumers.

In summary, this study proposes a four-factor initial trust formation framework based on the dynamic trust framework and the technology acceptance model. This framework distinguishes between direct and indirect experience pathways, systematically revealing the multi-level influence mechanisms of prior experience on initial trust. Specifically, it includes: (1) System performance perception (direct experience source): perceived usefulness and perceived flaws reflect individuals' performance judgments formed through direct operational experience; (2) System safety perception (direct experience source): safety risk perception and privacy risk perception reflect individuals' subjective assessments of potential risks and safety; (3) Social learning (indirect experience source): others' attitudes and social information shape individual trust through social influence; (4) Professional background (indirect experience source): as a key moderating factor, it reflects differences in individuals' professional knowledge and experience and may play a differential role between the above variables and initial trust. By integrating these four types of factors, this paper aims to systematically explain the differences and sources of initial trust in autonomous driving among different groups through prior experience.

1.2.1 Performance Perception: Perceived Usefulness and Perceived Flaws

The dynamic trust framework [?, ?] posits that individuals' subjective perception of autonomous driving system performance is an important influencing factor of initial trust, with perceived usefulness and perceived flaws being the two most studied core dimensions. Perceived usefulness refers to the degree to which individuals believe that using an autonomous driving system can improve driving performance [?, ?, ?], while perceived flaws refer to the perception of potential system defects [?, ?]. According to the technology acceptance model, perceived usefulness not only significantly influences technology acceptance intention but also largely does so through trust [?, ?]. Autonomous driving trust theory also emphasizes that initial trust largely depends on perceived system performance [?, ?, ?]. Although previous research has mostly focused on perceived usefulness of technology, perceived flaws are equally crucial when making trust judgments.

Therefore, perceived usefulness and perceived flaws, as key performance-based variables, directly shape individuals' initial trust in autonomous driving systems. When consumers perceive higher usefulness, they generally hold higher initial trust in autonomous driving systems [?, ?]. Conversely, if consumers perceive more flaws, they tend to hold negative attitudes toward autonomous driving system performance, thereby reducing initial trust [?, ?].

Thus, the following hypotheses are proposed:

H1: Perceived usefulness positively influences the initial trust of both professionals and non-professionals in autonomous vehicles.

H2: Perceived flaws negatively influence the initial trust of both professionals and non-professionals in autonomous vehicles.

1.2.2 Safety Perception: Safety Risk Perception and Privacy Risk Perception

Safety risk perception and privacy risk perception refer to individuals' concerns about personal safety and information security, respectively, reflecting their cognition and feelings about potential risks and safety [?, ?, ?]. Recent research indicates that human-machine trust has a safety dimension, meaning people trust machines because they believe machines will not threaten their personal and privacy safety [?, ?]. Conversely, when safety cannot be adequately guaranteed, consumers show persistent concerns about potential risks [?, ?]. For example, a Deloitte China (2019) survey showed that 42% of consumers have concerns about biometric data sharing mechanisms.

Safety risk perception is a key factor influencing initial trust. Studies have shown that when individuals perceive higher safety risks, their initial trust in autonomous vehicles significantly decreases [?, ?, ?], and this trend shows consistency across age groups [?, ?].

Privacy risk is also an important concern for consumers. Consumers generally worry about the misuse or unauthorized access of personal data by car manufacturers and insurance companies [?, ?, ?]. For instance, a study of American drivers showed that about one-third of respondents expressed serious concerns about privacy risks resulting from data misuse [?, ?].

However, the impact of privacy risk perception on initial trust remains controversial. Ma et al. (2020) found that for knowledge-rich adult groups, privacy risk perception was negatively correlated with initial trust in autonomous school buses, but no similar effect was observed in children with insufficient prior experience. Zhang et al. (2019) found no significant relationship between privacy risk perception and initial trust among Chinese drivers. These findings suggest that the impact of privacy risk may be moderated by certain boundary conditions, with inconsistent results across age groups indicating that prior experience may play a key role.

Therefore, this study further explores the influence of safety risk perception and privacy risk perception on initial trust in autonomous vehicles and proposes the following hypotheses:

H3: Safety risk perception negatively influences the initial trust of both professionals and non-professionals in autonomous vehicles.

H4: Privacy risk perception negatively influences professionals' initial trust in autonomous vehicles but has a weaker effect on non-professionals.

1.2.3 Social Influence

Social influence refers to an individual's perception of whether important others (e.g., family, friends) support a particular behavior [?, ?]. In the formation of technology acceptance and trust, others' opinions are an important source of prior experience [?, ?]. In the initial stage, individuals often lack direct interaction experience, so their trust in autonomous driving systems is mainly based on others' descriptions or media reports [?, ?]. Studies show that when autonomous driving systems are associated with well-known brands, consumers have higher trust in them [?, ?, ?]. Additionally, if a brand image is perceived as having high warmth or high competence characteristics, consumer trust is enhanced [?, ?].

Empirical research further validates the key role of social influence in shaping initial trust in autonomous vehicles. Zhang et al. (2020) found that social influence affects individuals' intention to use autonomous vehicles through initial trust. However, this finding differs from other technology acceptance studies [?, ?, ?], possibly because the autonomous vehicles studied at that time had not yet been fully commercialized. In the absence of direct experience, individuals' cognitive evaluations of automated technology may be unstable and more susceptible to media or peer opinions. Therefore, this study aims to re-evaluate the role of social influence in autonomous driving trust and proposes the following hypothesis:

H5: Social influence positively influences the initial trust of both professionals and non-professionals in autonomous vehicles.

1.3 Professional Background: Trust Differences Between Professionals and Non-Professionals

Existing research indicates that the strongest influencing factor in trust formation is an individual' s understanding of automated systems, which has a greater impact than system performance and reliability, while prior experience plays an important role in promoting this understanding [?, ?]. Professionals in the autonomous driving industry represent a group with high prior experience; they are more familiar with autonomous vehicles, can form reasonable expectations, and maintain stable trust. In contrast, ordinary consumers, due to limitations in relevant knowledge and experience, are more susceptible to superficial cues and often form higher but more fragile initial trust [?, ?, ?].

In the early stages of trust formation, professionals can better identify system performance boundaries and potential risks, showing a more cautious trust attitude [?, ?]. For example, experienced drivers using autonomous driving systems are more likely to maintain attention on the road or dashboard rather than engaging in distracting activities like using mobile phones, reflecting their sustained attention to system safety and reliability [?, ?]. In contrast, non-professionals lack prior experience and understanding of system operation principles, making them more dependent on intuitive system performance and direct feedback [?, ?]. Due to their inability to identify system limitations and potential risks (such as privacy issues), non-professionals tend to overestimate system performance and safety, showing excessive trust [?, ?, ?]. However, when systems perform poorly in critical situations, trust often collapses rapidly [?, ?, ?], and the higher the initial trust, the more dramatic the collapse [?, ?].

Individual differences caused by different professional backgrounds may be even more pronounced when assessing privacy risks, but current research has paid insufficient attention to this issue. According to the dynamic trust framework, objective system and contextual information must be processed by individuals into subjective perceptions before affecting initial trust [?, ?]. Individuals with different experience and knowledge levels interpret privacy risks differently [?, ?]. For example, people who have experienced privacy breaches show higher sensitivity to privacy risks [?, ?]. Therefore, this study hypothesizes that professional background moderates the effect of privacy risk perception on initial trust in autonomous driving systems: non-professionals, due to insufficient prior experience, may have lower privacy risk perception, but when privacy risks contradict their expectations, their initial trust fluctuates more dramatically. In contrast, professionals, having more reasonable expectations of privacy risks, maintain relatively stable initial trust levels. Recognizing these group differences is crucial during autonomous system design and promotion to ensure users receive appropriate information support and establish reasonable trust levels [?, ?].

Based on the above discussion, the following hypotheses are proposed:

H6: Privacy risk perception and professional background interact to influence initial trust in autonomous vehicles. Compared to professionals, non-professionals have lower privacy risk perception and exhibit higher initial trust.

H7: Privacy risk level can influence initial trust through privacy risk perception, with professional background moderating this relationship.

1.4 Overview of the Studies

In summary, this study aims to explore differences between professionals and non-professionals in initial trust in autonomous vehicles and its influencing factors. The research focuses on three core questions: What differences exist between professionals and non-professionals in initial trust in autonomous vehicles? How do subjective perceptual characteristics influence initial trust, and how does this influence differ between professionals and non-professionals? Can intervention methods bridge the gap in initial trust between professionals and non-professionals regarding autonomous vehicles?

To answer these questions, Study 1 first explores the factors influencing initial trust in autonomous vehicles and analyzes differences between professionals and non-professionals. Study 2 validates Study 1’ s findings by manipulating privacy risk levels. Study 3 further investigates whether non-professionals’ trust fluctuations can be attributed to enhanced privacy risk sensitivity through experimental intervention.

2 Study 1: Factors Influencing Initial Trust in Autonomous Vehicles: Differences Between Professionals and Non-Professionals

Study 1 conducted a questionnaire survey to explore differences between professionals and non-professionals in initial trust in autonomous vehicles and examine how perceptual characteristics influence initial trust.

2.1.1 Participants

This study recruited 200 professionals from autonomous driving companies through targeted recruitment and 601 non-professionals through the Credamo platform, collecting a total of 801 questionnaires. To ensure data quality, attention check questions were included, with 735 responses passing (92% pass rate). Additionally, to control for driving experience, participants without driver’ s licenses (35 people, 4.8%) were excluded from the analysis.

Participants with junior high school education (1 person, 0.1%) and those with high school/technical secondary school/technical school/vocational high school education (12 people, 1.6%) were also excluded due to small sample sizes. The final sample consisted of 689 valid participants (86% overall validity rate), including 165 professionals and 524 non-professionals.

To test for demographic differences between the two groups, we compared gender, age, education level, and driving experience. Chi-square tests showed no significant age difference between groups (^{2} g (3) = 5.3, p g = 0.152), but significant differences in gender (^{2}g d (1) = 82.6, pg d < 0.001), education (^{2} d c (2) = 111.0, p g < 0.001), and driving experience (^{2} c (4) = 20.7, p c < 0.001). In subsequent analyses, age, gender, education, and driving experience were controlled as covariates. Detailed demographic information for both groups is provided in Supplementary Table 2 .

2.1.2 Measures

All scales used in this study were translated from established scales used in previous research and measured using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) (see Supplementary Table 1).

Perceived Usefulness. Adopted from the perceived usefulness scale developed by Davis et al. (1989) and used by Zhang et al. (2020). This scale consists of 5 items. In this study, Cronbach' s $\alpha = 0.75$.

Perceived Flaws. Adopted from the perceived flaws scale developed by Ma et al. (2020). This scale consists of 2 items. In this study, Cronbach' s $\alpha = 0.59$.

Safety Risk Perception. Adopted from the safety risk perception scale developed by Zmud et al. (2016) and used by Zhang et al. (2019). This scale consists of 2 items. In this study, Cronbach' s $\alpha = 0.88$.

Privacy Risk Perception. Adopted from the privacy risk perception scale developed by Kyriakidis et al. (2015) and used by Zhang et al. (2019). This scale consists of 3 items. In this study, Cronbach' s $\alpha = 0.94$.

Social Influence. Adopted from the social influence scale used by Zhang et al. (2020). This scale consists of 3 items, with 2 items from Osswald et al. (2012) and 1 item from Madigan et al. (2017). In this study, Cronbach' s $\alpha = 0.82$.

Initial Trust. Adopted from the trust scale developed by Choi and Ji (2015) and used by Zhang et al. (2020) and Ma et al. (2020). This scale consists of 3 items. In this study, Cronbach' s $\alpha = 0.90$.

2.1.3 Procedure

Participants first learned about the experiment and signed informed consent forms. They then read a brief introduction about SAE Level 3 autonomous vehicles. The experimenter emphasized that the vehicles could perform driving tasks such as lane keeping and changing but still required human intervention in complex scenarios. Subsequently, participants completed questionnaires measuring perceived usefulness, perceived flaws, safety and privacy risk perception, social influence, and initial trust. Finally, demographic information including age, gender, education level, driver' s license status, and driving experience was collected. All participants received predetermined compensation upon completion.

2.2.1 Common Method Bias (CMB)

Harman's single-factor test was used to assess common method bias. The results showed 2 factors with eigenvalues greater than 1, with the first factor explaining 45.80% of the variance, below the 50% threshold, indicating no serious common method bias problem [**?**, **?**, **?**].

2.2.2 Descriptive Statistics and Group Differences

Means and standard deviations for both groups are presented in Table 1. Independent samples t-tests were conducted on initial trust, perceived usefulness, perceived flaws, safety risk perception, privacy risk perception, and social influence between the two groups. Due to unequal sample sizes and variances, Welch' s t-tests were used.

Results showed that professionals' initial trust in autonomous vehicles (M = 3.14, SD = 1.00) was significantly lower than non-professionals' (M = 4.04, SD = 0.74), t(223) = -10.71, $p < .001$, Cohen' s d = -1.03. Professionals' perceived usefulness (M = 3.51, SD = 0.96) was significantly lower than non-professionals' (M = 4.08, SD = 0.56), t(200) = -7.30, $p < 0.001$, Cohen' s d = -0.73. Professionals' perceived flaws (M = 3.70, SD = 0.87) were significantly higher than non-professionals' (M = 2.84, SD = 0.98), t(306) = 10.83, $p < 0.001$, Cohen' s d = 0.94. Professionals' safety risk perception (M = 3.98, SD = 1.03) was significantly higher than non-professionals' (M = 2.69, SD = 1.20), t(317) = 13.44, $p < 0.001$, Cohen' s d = 1.15. Professionals' privacy risk perception (M = 3.88, SD = 1.19) was significantly higher than non-professionals' (M = 2.44, SD = 1.21), t(279) = 13.56, $p < 0.001$, Cohen' s d = 1.21. Professionals' social influence (M = 3.34, SD = 0.97) was significantly lower than non-professionals' (M = 4.09, SD = 0.72), t(224) = -9.20, $p < 0.001$, Cohen' s d = -0.88.

2.2.3 Correlation Analysis

Further correlation analysis was conducted to examine relationships among the six variables (perceived usefulness, safety risk perception, privacy risk perception, perceived flaws, social influence, and initial trust) (see Table 1). Results showed that perceived usefulness and social influence were significantly positively correlated with initial trust in both groups, while safety risk perception, privacy risk perception, and perceived flaws were significantly negatively correlated with initial trust.

2.2.4 Regression Analysis

Hierarchical linear regression was conducted with initial trust as the dependent variable, perceived usefulness, perceived flaws, safety risk perception, privacy risk perception, and social influence as independent variables, and professional background (dummy-coded) as a moderator. The model included two-way interaction terms between each independent variable and professional background, and examined the effects on initial trust while controlling for gender, age, education, and driving experience (all dummy-coded). Control variables were entered in the first layer, and other predictors were entered in the second layer. The predictive effects of variables and interaction terms on initial trust are shown in Table 2.

Results showed a significant two-way interaction between privacy risk perception and professional background (β = -0.06, p = 0.038), indicating that the effect of privacy risk perception on initial trust differed between groups. Simple slope tests (see Figure 1 [Figure 1: see original paper]) showed that professionals' privacy risk perception significantly negatively predicted initial trust (simple slope = -0.21, t = -3.59, p < 0.001), but this effect was nonsignificant for non-professionals (simple slope = -0.06, t = -1.58, p = 0.114).

At the main effect level, perceived usefulness (β = 0.18, p < 0.001) and social influence (β = 0.51, p < 0.001) significantly positively predicted initial trust. Safety risk perception (β = -0.22, p < 0.001) significantly negatively predicted initial trust. The effects of perceived flaws (β < -0.01, p = 0.643) and professional background (β = 0.01, p = 0.148) on initial trust were nonsignificant.

2.3 Discussion

Study 1 aimed to explore differences and mechanisms between professionals and non-professionals in initial trust in autonomous vehicles. Based on the dynamic trust framework [?, ?] and the technology acceptance model (TAM, Davis et al., 1989), Study 1 examined four types of factors: system performance perception (perceived usefulness, perceived flaws), system safety perception (safety risk perception, privacy risk perception), social learning (social influence), and a key operator characteristic variable—professional background.

Overall results showed that non-professionals had significantly higher initial trust than professionals. They tended to overestimate system usefulness, underestimate system risks and flaws, and were more susceptible to social influence. This suggests that in the early stages of trust formation, professionals typically adopt a cautious, conservative attitude, while non-professionals may show excessive trust due to lack of technical knowledge and risk awareness.

Further analysis revealed group differences in how privacy risk perception affected initial trust (supporting H6). For professionals, privacy risk perception significantly negatively predicted initial trust; for non-professionals, this effect was nonsignificant (supporting H4). This difference may stem from professionals' greater sensitivity to privacy risks [?, ?]. In contrast, non-professionals lack understanding of system mechanisms and have insufficient perception of potential privacy risks, resulting in weaker effects on their trust levels. This result also suggests that previous studies (e.g., Ma et al., 2020; Zhang et al., 2019) that found no significant effect of privacy risk perception on initial trust may be related to the fact that autonomous vehicles were not yet widespread and participants were not sufficiently familiar with them.

Regarding other predictors, social influence, perceived usefulness, and safety risk perception all significantly predicted initial trust, while perceived flaws did not. Consistent with Zhang et al. (2020), this study found social influence to be the strongest predictor (supporting H5). This indicates that in the early stages of trust formation, individuals lack sufficient information and direct experience about autonomous vehicles, making media and others' opinions the primary source of prior experience. Perceived usefulness positively predicted initial trust (supporting H1), aligning with the core assumption of the technology acceptance model (Davis et al., 1989) that perceived usefulness is a key driver of technology adoption and trust formation. Safety risk perception significantly negatively predicted initial trust (supporting H3), consistent with existing research [?, ?, ?, ?], showing that even without actual negative experience, safety concerns can reduce individuals' initial trust.

In contrast, perceived flaws did not significantly predict initial trust (not supporting H2), differing from Ma et al. (2020). This may be related to sample characteristics and scenario differences. Ma et al. (2020) focused on parents' trust in autonomous school buses, a perspective different from ordinary passengers. Additionally, children' s prior experience differs from adults, which may lead to different trust judgments. Moreover, the low reliability of the perceived flaws scale in this study may have contributed to its nonsignificant prediction of initial trust.

In summary, Study 1 validated the key roles of system performance perception, system safety perception, and social influence in initial trust formation, supporting the main hypotheses of the dynamic trust framework and technology acceptance model. The study also revealed group differences in privacy risk perception, showing that professional background has a moderating effect in trust formation. Study 2 will further examine this group difference by manipulating privacy risk levels.

3 Study 2: The Impact of Privacy Risk Perception on Initial Trust: The Moderating Role of Professional Background

In Study 1, we found a significant interaction between privacy risk perception and professional background on initial trust. To further validate the relationship between privacy risk perception and professional background and its impact on initial trust, Study 2 employed an online experiment recruiting both professionals and non-professionals as participants. We first manipulated privacy risk levels for both groups, then measured their privacy risk perception and initial trust in autonomous vehicles.

3.1.1 Participants

Based on calculations using G*Power software [**?**, **?**], with an expected effect size of f = 0.25, statistical power of 1 -β = 0.95, and significance level of α = 0.05, the recommended sample size was N = 106. We recruited 114 professionals from autonomous driving companies through targeted recruitment and 107 non-professionals through the Credamo platform, collecting a total of 221 questionnaires. To ensure data quality, attention check questions were included, with 192 responses passing (87% pass rate). Participants without driver' s licenses (7 people, 3.6%) were excluded to control for driving experience. Participants with high school/technical secondary school/technical school/vocational high school education (2 people, 1.0%) were also excluded due to small sample size. The final sample consisted of 183 valid participants (92% overall validity rate), including 90 professionals and 93 non-professionals.

To test for demographic differences between groups, we compared gender, age, education, and driving experience. Chi-square tests showed significant differences in gender (^{2}g d (1) = 34.9, pg d < 0.001), age (^{2} g (3) = 31.8, p g < 0.001), education (^{2} d c (2) = 46.6, p g < 0.001), and driving experience (^{2} c (4) = 58.8, p c < 0.001). In subsequent analyses, age, gender, education, and driving experience were controlled for both professionals and non-professionals. Detailed demographic information for both groups is provided in Supplementary Table 3 .

3.1.2 Procedure and Measures

After learning about the experiment and signing informed consent forms, participants in both groups read experimental materials about low and high privacy risk conditions. We manipulated privacy risk levels to influence participants' privacy risk perception. Previous research has shown that exposure to reading materials highlighting potential privacy risks may enhance individuals' privacy risk perception [**?**, **?**].

At the beginning of the experiment, participants were informed that autonomous vehicles need to collect and share large amounts of data through sensing devices to ensure driving safety, system reliability, and optimal performance. Participants then read data security management cases from two companies—Company Z (low privacy risk) and Company H (high privacy risk)—and evaluated their autonomous vehicles.

In the low privacy risk condition, the case description was: "Company Z attaches great importance to data security management. To improve data confidentiality and prevent unreasonable use of personal information, Company Z has established a data collection information management platform, uses dedicated encrypted channels for data transmission, and operates core businesses on private clouds. Personal user privacy data, including facial feature information, vehicle location information, and driving habits, are desensitized according to the relevant provisions of the Personal Information Protection Law of the People' s Republic of China."

In the high privacy risk condition, the case description was: "Company H recently issued a statement that the company suffered a hacker attack, resulting in user data leakage. Hackers obtained personal information of some drivers through online mobile applications, including names, phone numbers, points of interest, vehicle trajectories, personal social media accounts, family information, subscribed packages, personal avatars, and search history. This data leakage incident reflects that Company H' s data security protection still has room for improvement."

Participants used the same measurement items as in Study 1 to assess their privacy risk perception on a 5-point Likert scale (1 = completely disagree, 5 = completely agree), with higher scores indicating higher privacy risk perception (Cronbach' s $\alpha = 0.95$ in this study). Initial trust was also measured using the same items as in Study 1 on a 5-point Likert scale, with higher scores indicating higher initial trust (Cronbach' s $\alpha = 0.95$ in this study). Finally, participants completed demographic information and received compensation.

3.2.1 Manipulation Check for Privacy Risk Perception

Descriptive statistics for all variables are presented in Table 3. A 2 (professional background: professional vs. non-professional) × 2 (privacy risk: high vs. low) mixed-design ANOVA on privacy risk perception showed a significant main effect of privacy risk level, $F(1, 181) = 290.35$, $p < 0.001$, $p^2 = 0.62$. Privacy risk perception was significantly higher in the high privacy risk condition ($M = 4.36$, $SD = 0.82$) than in the low privacy risk condition ($M = 3.05$, $SD = 1.49$). The main effect of professional background was also significant, $F(1, 181) = 93.91$, $p < 0.001$, $p^2 = 0.34$, with professionals ($M = 4.27$, $SD = 0.97$) showing significantly higher privacy risk perception than non-professionals ($M = 3.15$, $SD = 1.47$).

A significant interaction between privacy risk level and professional background emerged, $F(1, 190) = 201.30$, $p < 0.001$, $p^2 = 0.51$. Simple effects analysis showed that for non-professionals, privacy risk perception was significantly higher in the high privacy risk condition ($M = 4.31$, $SD = 0.79$) than in the low privacy risk condition ($M = 2.00$, $SD = 1.01$), $F(1, 181) = 473.07$, $p < 0.001$. For professionals, privacy risk perception was also higher in the high privacy risk condition ($M = 4.41$, $SD = 0.86$) than in the low privacy risk condition ($M = 4.14$, $SD = 1.06$), but the difference was smaller, $F(1, 181) = 6.28$, $p = 0.013$.

3.2.2 Effects of Professional Background and Privacy Risk Perception on Initial Trust

To examine the effects of professional background and privacy risk perception on initial trust, this study used linear mixed-effects models (LMM). Considering that different individuals may have different dispositional trust levels, LMM can distinguish between individual differences (random effects) and experimental manipulation effects (fixed effects), yielding more precise and generalizable inferences. The GAMLj module in jamovi 2.6.26 was used for LMM modeling, with participant ID as a random effect and professional background, privacy risk perception, and their interaction as fixed effects, while controlling for age, gender, education, and driving experience. The model showed an AIC value of 760.07, with predictive effects of variables and interactions on initial trust presented in Table 4 .

Analysis revealed a significant interaction between professional background and privacy risk perception (β = 0.73, p < 0.001), indicating that the effect of privacy risk perception on initial trust differed between groups. Simple slope tests (see Figure 2 [Figure 2: see original paper]) showed that for professionals, increased privacy risk perception significantly reduced initial trust (simple slope = -0.18, p = 0.002). For non-professionals, the increase in privacy risk perception led to a more dramatic decline in initial trust (simple slope = -0.92, p < 0.001). This suggests that professionals' initial trust is relatively stable, while non-professionals experience more drastic trust declines when facing privacy concerns.

3.2.3 Testing a Moderated Mediation Model: Effects of Privacy Risk Level on Initial Trust

To further explain the trust mechanisms of professionals and non-professionals, following the testing method proposed by Wen and Ye (2014), this study examined the mediating role of privacy risk perception in the relationship between privacy risk level and initial trust, and whether professional background moderated the first half of this mediation path. SPSS macro PROCESS Model 1 was used to test whether the effect of privacy risk level on initial trust was moderated by professional background, controlling for gender, age, education, and driving experience. Results showed that privacy risk level significantly affected initial trust (β = -2.32, p < 0.001, 95% CI [-2.55, -2.09]), and the interaction between privacy risk level and professional background on initial trust was significant (β = 2.12, p < 0.001, 95% CI [1.78, 2.45]), indicating that professional background moderated the effect of privacy risk level on initial trust.

Next, a moderated mediation model was established. SPSS macro PROCESS Model 7 was used to test the moderating effect of professional background, controlling for gender, age, education, and driving experience. First, the effect of privacy risk level on privacy risk perception was tested. Results showed that privacy risk level significantly affected privacy risk perception (β = 2.31, p <

0.001, 95% CI [2.05, 2.56]), and the interaction between privacy risk level and professional background on privacy risk perception was significant (β = -2.04, p < 0.001, 95% CI [-2.40, -1.67]). Second, the effect of privacy risk level on initial trust through privacy risk perception was tested. Results showed that the direct effect of privacy risk level on initial trust was significant (β = -0.60, p < 0.001, 95% CI [-0.79, -0.41]), and the effect of privacy risk perception on initial trust was significant (β = -0.52, p < 0.001, 95% CI [-0.59, -0.44]). Model results are presented in Figure 3 [Figure 3: see original paper].

Overall, the partial mediating effect of privacy risk perception between privacy risk level and initial trust was moderated by professional background. For professionals, the indirect effect of privacy risk level on initial trust through privacy risk perception was nonsignificant, with an indirect effect of -0.14, 95% CI [-0.28, 0.01]. For non-professionals, this indirect effect was significant, with an indirect effect of -1.20, 95% CI [-1.42, -0.98]. Results are presented in Table 5 .

3.3 Discussion

Study 2 further examined the role of privacy risk perception in initial trust formation and tested the moderating effect of professional background by manipulating privacy risk levels. Results showed that increased privacy risk perception reduced individuals' initial trust, with a significant interaction between professional background and privacy risk perception (supporting H6).

Specifically, under low privacy risk conditions, non-professionals showed high initial trust, possibly because they failed to fully consider potential risks from data collection, storage, and usage. Professionals, with relevant professional knowledge and experience, showed more cautious attitudes [**?**, **?**]. However, when privacy risk levels increased, non-professionals' initial trust declined significantly, even falling below that of professionals. This result aligns with Kraus et al. (2020), showing that when actual system performance contradicts expectations, ordinary users' trust levels fluctuate noticeably, while professionals' trust remains relatively stable.

Furthermore, the moderated mediation analysis supported H7, showing that privacy risk perception mediated the relationship between privacy risk level and initial trust, with professional background moderating the effect of privacy risk level on privacy risk perception. Specifically, non-professionals' privacy risk perception fluctuated significantly with changes in privacy risk level, which in turn affected initial trust. In contrast, professionals' privacy risk perception remained relatively stable, making the indirect effect nonsignificant. This finding aligns with Onnasch et al. (2023), suggesting that non-professionals rely more on externally provided information to form judgments about systems, making their initial trust more sensitive to contextual information.

Notably, Study 1 found that under natural conditions, privacy risk perception did not significantly predict non-professionals' initial trust, while Study 2, through experimental manipulation, found that non-professionals' initial trust declined significantly when privacy risk levels increased. This difference suggests that non-professionals tend to underestimate privacy risks in natural contexts, but when risks are made salient through manipulation, their privacy risk perception increases significantly, leading to noticeable changes in initial trust levels.

In summary, Study 2 validated the critical role of privacy risk perception in initial trust formation and revealed the moderating mechanism of professional background. In Study 3, we further explore whether enhancing non-professionals' sensitivity to privacy risks can effectively regulate their excessive trust in autonomous vehicles, thereby promoting more rational trust calibration.

4 Study 3: The Impact of Privacy Risk Perception on Non-Professionals' Initial Trust

In Study 2, we found that under experimental manipulation, increased privacy risk perception significantly reduced non-professionals' initial trust. However, under natural conditions, privacy risk perception was not a significant predictor of non-professionals' initial trust. This change may be attributed to the manipulation of privacy risk conditions enhancing non-professionals' sensitivity to privacy risks. To further explore the relationship between non-professionals' privacy risk perception and initial trust, Study 3 sequentially exposed non-professional participants to a control condition (without privacy risk awareness activation), a low privacy risk condition, and a high privacy risk condition, and measured their initial trust in autonomous vehicles, thereby addressing research question 3.

4.1.1 Participants

Based on calculations using G*Power software [**?**, **?**], with an expected effect size of f = 0.25, statistical power of 1 -β = 0.95, and significance level of α = 0.05, the recommended sample size was N = 84. We recruited 200 non-professionals through the Credamo platform. To ensure data quality, attention check questions were included, with 156 responses passing (78% pass rate). All participants held valid driver' s licenses. One participant with high school/technical secondary school/technical school/vocational high school education (0.2%) was excluded due to small sample size. The final sample consisted of 155 valid participants (78% validity rate). Detailed demographic information is provided in Supplementary Table 4.

4.1.2 Procedure and Measures

The experiment consisted of two phases. Phase 1 replicated the procedure of Study 1. In this part, participants' privacy risk awareness was not activated (control condition). Participants first read an introduction about SAE Level 3 autonomous vehicles, understanding their capabilities and the necessity for driver intervention in specific situations. They then evaluated their privacy risk perception and initial trust levels based on their own experience.

After a one-day interval, Phase 2 began, with experimental procedures referencing Study 2' s design. Participants were first informed that autonomous vehicles need to collect and share large amounts of data through sensing devices to ensure safety, reliability, and optimal performance. They then read data security management practices of Company Z (low privacy risk condition) and Company H (high privacy risk condition) and evaluated their privacy risk perception and initial trust.

Participants used the same scale as in Study 1 to rate privacy risk perception (5-point Likert scale, 1 = completely disagree, 5 = completely agree), with higher scores indicating higher privacy risk perception (Cronbach' s $\alpha = 0.94$ in this study). Initial trust was also measured using the same items as in Study 1 (5-point Likert scale, 1 = completely disagree, 5 = completely agree), with higher scores indicating higher initial trust (Cronbach' s $\alpha = 0.93$ in this study).

Finally, participants completed demographic information and received compensation.

4.2.1 Manipulation Check for Privacy Risk Perception

Descriptive statistics for Study 3 variables are presented in Table 6 . Repeated measures ANOVA on privacy risk perception showed that the manipulation significantly affected participants' privacy risk perception, $F(2, 308) = 686.00$, $p < 0.001$, $p^2 = 0.82$. Further Bonferroni post-hoc tests showed that under low privacy risk conditions, non-professionals' privacy risk perception was significantly lower than in the control condition ($M_{w} = 1.83$, $SD = 0.80$; $M_{c} = 2.05$, $SD = 1.02$), $p = 0.005$. Under high privacy risk conditions, non-professionals' privacy risk perception was significantly higher than in the control condition ($M_{g} = 4.41$, $SD = 0.55$), $p < 0.001$.

4.2.2 Effects of Privacy Risk Perception on Initial Trust

To examine the effect of privacy risk perception on initial trust across the three risk scenarios, this study used linear mixed-effects models (LMM). The GAMLj module in jamovi 2.6.26 was used for LMM modeling, with participant ID as a random effect and privacy risk scenario (control, low-risk, and high-risk conditions, dummy-coded) and privacy risk perception as fixed effects, while controlling for age, gender, education, and driving experience. The model showed an AIC value of 582.00, with predictive effects on initial trust presented in Table 7 .

Analysis showed that privacy risk perception significantly affected non-professionals' initial trust ($\beta = -0.33$, $p < 0.001$). In the low-risk scenario, non-professionals' initial trust did not significantly decline compared to the control condition ($\beta < -0.01$, $p = 0.942$). However, in the high-risk scenario, initial trust significantly decreased compared to the control condition (β = -1.65, p < 0.001). Further Bonferroni post-hoc tests showed that under low privacy risk conditions, non-professionals' initial trust did not significantly differ from the control condition (M w = 4.40, SD = 0.43; Mc = 4.33, SD = 0.45), p > 0.999. Under high privacy risk conditions, non-professionals' initial trust was significantly lower than in both the control and low-risk conditions (M g = 1.89, SD = 0.60), ps < 0.001 (see Figure 4 [Figure 4: see original paper]).

4.3 Discussion

To explore changes in non-professionals' initial trust under fluctuating privacy risks, Study 3 manipulated privacy risk perception levels. Results showed that compared to the control condition, non-professionals' privacy risk perception significantly decreased under low privacy risk conditions, but initial trust did not change significantly. However, under high privacy risk conditions, privacy risk perception significantly increased and initial trust significantly decreased. This reveals non-professionals' asymmetric sensitivity to privacy risk information.

Specifically, under low privacy risk conditions, although non-professionals' privacy risk perception significantly decreased, their initial trust remained stable. This suggests that low-risk information is insufficient to trigger significant trust changes, possibly because non-professionals have low baseline expectations of privacy risks in autonomous vehicles. In other words, they are insensitive to low-risk information, showing a degree of over-trust.

In contrast, under high privacy risk conditions, non-professionals' privacy risk perception significantly increased, accompanied by a significant decrease in initial trust. This change indicates that non-professionals are highly sensitive to high-risk information, particularly when privacy security is clearly threatened, leading them to sharply reduce their initial trust in autonomous vehicles [**?**, **?**]. This aligns with previous research showing that when actual risks exceed expectations, trust often declines significantly [**?**, **?**, **?**].

This "low-sensitivity—high-sensitivity" asymmetric pattern reveals non-professionals' inaccurate perception of privacy risks and their tendency toward over-trust. This study suggests that trust bias can be improved through information guidance: on one hand, in low-risk scenarios, moderate risk reminders can enhance non-professionals' risk awareness and prevent them from overlooking potential privacy threats; on the other hand, in high-risk scenarios, non-professionals should be helped to form rational risk judgments to avoid excessive distrust due to fear or uncertainty. Therefore, through reasonable information guidance and risk reminders, non-professionals can be helped to form appropriate trust levels under different risk conditions, thereby promoting safe and stable human-machine relationships.

5 General Discussion

Based on the dynamic trust framework, this study systematically explored initial trust in autonomous vehicles and its influencing factors. Referencing the technology acceptance model, we constructed a "four-factor framework" explaining autonomous driving initial trust formation mechanisms and group differences from four aspects: system performance, risk perception, social influence, and professional background. Through three studies, we examined the role of privacy risk perception in initial trust formation and the moderating effect of professional background.

Study 1, based on an online questionnaire survey, found that non-professionals had significantly higher initial trust than professionals, overestimating system performance, underestimating system flaws and risks, and being more susceptible to social influence. Regression analysis showed an interaction between privacy risk perception and professional background: privacy risk perception only significantly predicted professionals' initial trust. Study 2 experimentally manipulated privacy risk levels, further validating the mediating role of privacy risk perception in initial trust formation and the moderating role of professional background. Results showed that elevated privacy risk levels significantly enhanced non-professionals' privacy risk perception and reduced their initial trust, while professionals' trust levels remained relatively stable. These results reveal differential responses between professionals and non-professionals to privacy risk changes. Study 3 built on the first two studies and further revealed non-professionals' asymmetric response to privacy risk information: under low privacy risk conditions, although privacy risk perception significantly increased, initial trust showed no significant change; under high privacy risk conditions, privacy risk perception significantly increased and initial trust significantly decreased. This "low-sensitivity—high-sensitivity" response pattern reflects the imbalance in non-professionals' processing of privacy risk information. Overall, this study found that privacy risk perception is an important psychological mechanism explaining initial trust differences between groups, and that professional background further shapes different trust formation pathways by influencing risk sensitivity and information processing methods.

5.1 Non-Professionals' Tendency Toward Over-Trust

The first important finding of this study is the revelation of group differences in autonomous driving initial trust levels: compared to professionals, non-professionals have higher initial trust in autonomous vehicles and show a tendency toward over-trust. The dynamic trust framework suggests that prior experience is an important factor influencing initial trust [**?**, **?**]. Study 1' s results confirm this view: professionals, with rich prior experience, can more clearly identify the limitations and potential risks of autonomous driving systems [**?**, **?**], and therefore behave more cautiously when facing automated technology [**?**, **?**, **?**]. In contrast, non-professionals, lacking relevant experience, tend to overestimate system performance and underestimate potential risks and flaws, making them more prone to over-trust [?, ?, ?, ?]. This finding provides new empirical evidence for differences among autonomous vehicle user groups, showing that professionals typically adopt more cautious attitudes in the early stages of trust formation, while non-professionals may exhibit over-trust.

5.2 Group Differences in Factors Influencing Initial Trust

Study 1, through an online questionnaire survey, examined factors influencing initial trust under natural conditions for professionals and non-professionals. Based on the dynamic trust framework and technology acceptance model, Study 1 focused on four types of variables: system performance perception, system safety perception, social influence, and professional background. Results showed significant differences between groups in the trust formation process.

First, privacy risk perception only significantly predicted professionals' initial trust, with no significant effect on non-professionals. This indicates that compared to professionals, non-professionals lack necessary knowledge and experience, making them prone to overlook critical but less obvious issues like privacy risks [?, ?]. This finding aligns with Ma et al. (2020): for knowledge-rich adults, privacy risk perception showed a significant negative correlation with initial trust, but no similar relationship was observed in children. Zhang et al. (2019) found no significant relationship between privacy risk perception and autonomous driving initial trust, interpreting this as privacy issues being relatively less important for Chinese participants. Notably, that study' s sample was recruited through convenience sampling (face-to-face at public parking lots), with nearly half of participants driving less than once per week—sample characteristics that may explain the nonsignificant results. Additionally, this study' s results show that under natural conditions, ordinary consumers have low sensitivity to privacy risks and tend to overlook potential privacy violations and their consequences when lacking sufficient prior experience. Overall, this study validates the interaction between professional background and privacy risk perception, showing that privacy risk' s effect on initial trust depends on experience differences, with non-professionals showing "risk insensitivity" due to insufficient experience.

Furthermore, social influence, perceived usefulness, and safety risk perception jointly predicted individuals' initial trust. This indicates that initial trust formation is a complex process influenced by multiple factors [?, ?, ?, ?]. These results support the importance of social influence [?, ?, ?] and perceptual characteristics [?, ?, ?] in autonomous driving trust, and emphasize that professional background, social influence, and subjective perceptions should be integrated into a unified analytical framework when analyzing trust formation. This study reveals differences in influencing factors between professionals and non-professionals, providing empirical support for building more explanatory trust models.

5.3 Trust Fluctuation Under Privacy Risk: Differential Responses Between Professionals and Non-Professionals

The second important finding of this study is that changes in privacy risk levels significantly affect individuals' initial trust, with professionals and non-professionals showing distinct response patterns. Study 2' s results show that increased privacy risk levels lead to decreased trust among professionals, but the magnitude remains relatively stable. Non-professionals' trust changes are more dramatic. This finding aligns with previous research showing that when systems do not clearly disclose their limitations, people tend to form high initial trust [?, ?], and when system performance fails to meet user expectations, trust levels may decline [?, ?]. More importantly, the higher the initial trust level, the greater the decline when system performance fails to meet expectations [?, ?]. Study 2 demonstrated that privacy risk level affects initial trust through privacy risk perception and revealed the moderating role of professional background.

5.4 Non-Professionals' Asymmetric Response to Privacy Risk Information

Building on the first two studies, Study 3 further revealed the asymmetry in non-professionals' processing of privacy risk information. Under low privacy risk conditions, although non-professionals' privacy risk perception significantly decreased, their initial trust level did not change significantly, indicating that low-risk information is insufficient to trigger trust adjustment. This may stem from non-professionals' low expectations of privacy risks and their insensitivity to low-risk cues, showing a degree of over-trust.

Under high privacy risk conditions, non-professionals' privacy risk perception significantly increased, accompanied by a significant decrease in initial trust. This result validates existing research: when actual risks exceed expectations, individual trust declines rapidly [?, ?, ?]. Especially when privacy security is clearly threatened, non-professionals significantly reduce their initial trust in autonomous vehicles [?, ?].

This asymmetry has important practical implications. Non-professionals' trust levels can be reasonably calibrated by enhancing privacy risk perception, thereby reducing their over-trust. When privacy-related information is lacking, non-professionals tend to make overly optimistic assessments of autonomous vehicle safety [?, ?, ?, ?]. Therefore, through reasonable risk reminders, public trust can be promoted to align more closely with the system' s actual level at the societal level.

5.5 Research Implications and Contributions

This study makes important contributions to understanding initial trust in autonomous vehicles. At the theoretical level, based on the dynamic trust framework and technology acceptance model, this study proposes a four-factor trust framework encompassing system performance, system safety, social influence, and professional background. This framework reveals the key role of prior experience in trust formation and provides a new explanatory perspective for analyzing differential trust responses among individuals with different backgrounds facing the same technology.

Second, this study systematically explored the influence of privacy risk perception on autonomous vehicle initial trust through three studies, revealing the moderating role of professional background. Findings show that professionals' initial trust is relatively stable, while non-professionals are more sensitive to privacy risk changes, especially under high privacy risk conditions where initial trust declines significantly. These results extend the dynamic trust framework, emphasize the critical role of privacy issues in technology acceptance processes, and provide theoretical foundations for privacy risk management [**?**, **?**, **?**].

This study also explored the potential role of risk reminders in calibrating non-professionals' trust expectations regarding autonomous vehicles. Results show that increasing non-professionals' privacy risk perception can effectively calibrate over-trust and narrow the initial trust gap with professionals. This finding provides empirical support for trust management strategies, particularly in raising privacy risk awareness. Reasonable risk reminders can effectively adjust non-professionals' trust expectations to be more realistic, which is crucial for calibrating public trust [**?**, **?**].

This study' s findings provide important references for autonomous vehicle companies to develop strategies to enhance consumer initial trust. The research emphasizes that companies should consider differences in prior experience, especially in contexts where technology is highly complex and privacy issues are prominent [**?**, **?**]. Non-professionals often hold optimistic attitudes toward privacy security, but their initial trust levels drop sharply when privacy breaches occur. Therefore, autonomous vehicle companies should prioritize strengthening data security and management measures to reduce public trust decline caused by data privacy incidents [**?**, **?**]. Additionally, strengthening consumer trust through social influence and media promotion, especially in the initial promotion stage, may be an effective trust enhancement strategy.

5.6 Limitations and Future Directions

This study only intervened on privacy risk and has not examined the role of other perceptual characteristics in initial trust differences between professionals and non-professionals. The perceived flaws scale showed low reliability; future research should develop more reliable and valid measurement tools to obtain more robust results. Additionally, this study only measured individuals' initial trust without involving deeper usage intention indicators such as acceptance attitudes or actual usage behavior. Given that initial trust is an important antecedent attitude variable for technology acceptance [**?**, **?**], future research could explore how to more effectively transfer and apply the technology acceptance model to autonomous driving contexts.

Furthermore, this study did not restrict professional tenure. The core focus was on differences in autonomous vehicle trust among individuals with different prior experiences [?, ?]. Although professionals generally have more prior experience, those with different tenures may differ in knowledge mastery and technology familiarity. Future research could further control for professional tenure or consider factors like technology familiarity to more precisely reveal the mechanisms through which prior experience affects trust.

Finally, this study' s participants were all from China, limiting the generalizability of the findings. Cultural differences may affect how individuals in different countries understand and evaluate autonomous vehicles [?, ?]. Future research could examine cultural differences in trust and explore how prior experience shapes trust in autonomous vehicles across different cultural contexts.

6 Conclusion

Based on the dynamic trust framework, this study proposes a four-factor initial trust model encompassing system performance, system safety, social influence, and professional background. Through three studies, we validated the critical role of professional background in initial trust formation and revealed the influence and mechanisms of privacy risk perception on initial trust. Study 1 found that non-professionals showed higher initial trust and a tendency toward over-trust. Under natural conditions, social influence, perceived usefulness, and safety risk perception were key predictors of initial trust. Privacy risk perception only predicted professionals' initial trust, not non-professionals' . Study 2, by manipulating privacy risk levels, further validated the mediating role of privacy risk perception among non-professionals and showed that under high privacy risk conditions, non-professionals' initial trust declined significantly. Study 3 revealed non-professionals'asymmetric response to privacy risk information: under low-risk conditions, trust did not change significantly, while under high-risk conditions, trust levels declined significantly. These results enrich the theoretical framework of autonomous vehicle initial trust, emphasize the core role of prior experience in trust formation, especially in explaining trust differences among individuals with different backgrounds. The study provides theoretical and empirical foundations for autonomous driving companies to design trust calibration strategies, highlighting that reasonable risk reminders help establish a safer and more reliable human-machine trust foundation in real-world environments.

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Appendix 1: Experimental Questionnaire Items

Perceived Usefulness - Autonomous vehicles can effectively meet my driving needs. - When using autonomous vehicles, I can simultaneously do other things in the car, such as eating, watching movies, using my phone, etc. - Using autonomous vehicles can reduce accident rates. - Using autonomous vehicles can alleviate my driving stress. - When I' m in poor driving condition (e.g., fatigued driving, drunk driving), autonomous vehicles are very useful.

Perceived Flaws - The driving performance of autonomous vehicles is relatively conservative and slow. - I worry that the autonomous system may malfunction and be difficult to repair.

Safety Risk Perception - I worry about the overall safety of autonomous vehicle technology. - I worry that malfunctions in autonomous vehicles may cause accidents.

Privacy Risk Perception - I worry that autonomous vehicles collect too much of my personal information. - I worry that autonomous vehicles use my personal information for other purposes without my authorization. - I worry that autonomous vehicles share my personal information with other companies without my authorization.

Social Influence - The opinions of people who are important to me will also like autonomous vehicles. - Overall, people I like will encourage me to use autonomous vehicles. - If my friends or family use autonomous vehicles, I am more likely to use them.

Initial Trust - Autonomous vehicles are reliable. - Autonomous vehicles are trustworthy. - Overall, I can trust autonomous vehicles.

Appendix 2: Demographic Information Tables

Supplementary Table 2: Demographic Information of Participants in Study 1 (N = 689)

Demographic Variable	Professionals (N = 165)	Non-Professionals (N = 524)
Age		
18-30 years	[percentage]	[percentage]
31-40 years	[percentage]	[percentage]
41-50 years	[percentage]	[percentage]

Demographic Variable	Professionals (N = 165)	Non-Professionals (N = 524)
51 years and above	[percentage]	[percentage]
Education		
Junior college	[percentage]	[percentage]
Bachelor' s degree	[percentage]	[percentage]
Master' s and above	[percentage]	[percentage]
Driving Experience		
1 year and below	[percentage]	[percentage]
1-3 years	[percentage]	[percentage]
4-6 years	[percentage]	[percentage]
7-9 years	[percentage]	[percentage]
10 years and above	[percentage]	[percentage]

Supplementary Table 3: Demographic Information of Participants in Study 2 (N = 183)

Demographic Variable	Professionals (N = 90)	Non-Professionals (N = 93)
Age		
18-30 years	[percentage]	[percentage]
31-40 years	[percentage]	[percentage]
41-50 years	[percentage]	[percentage]
51 years and above	[percentage]	[percentage]
Education		
Junior college	[percentage]	[percentage]
Bachelor' s degree	[percentage]	[percentage]
Master' s and above	[percentage]	[percentage]
Driving Experience		
1 year and below	[percentage]	[percentage]
1-3 years	[percentage]	[percentage]
4-6 years	[percentage]	[percentage]
7-9 years	[percentage]	[percentage]
10 years and above	[percentage]	[percentage]

Supplementary Table 4: Demographic Information of Non-Professional Participants in Study 3 (N = 155)

Demographic Variable	Percentage
Age	

Demographic Variable	Percentage
18-30 years	[percentage]
31-40 years	[percentage]
41-50 years	[percentage]
51 years and above	[percentage]
Education	
Junior college	[percentage]
Bachelor' s degree	[percentage]
Master' s and above	[percentage]
Driving Experience	
1 year and below	[percentage]
1-3 years	[percentage]
4-6 years	[percentage]
7-9 years	[percentage]
10 years and above	[percentage]

Note: Figure translations are in progress. See original paper for figures.