Frontiers in Traffic and Transportation Engineering (2025) **DOI: 10.23977/ftte.2025.050102**
Clausius Scientific Press, Canada **ISSN 2616-2334 Vol. 5 Num. 1**

Investigating the Determinants of Driver Trust in Semi-Autonomous Vehicle Systems: A Multidimensional Analysis

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Keywords: Semi-autonomous vehicles; Trust formation; System determinants; Psychometric questionnaire; Structural Equation Modeling (SEM)

Abstract: This study investigates the determinants of driver trust in semi-autonomous vehicles through an integrated theoretical framework. Building upon established automation trust models and empirical observations of current system deployments, we identify eight critical antecedents: system predictability, automation reliability, interface transparency, human-machine interaction design, anthropomorphism, contextual driving scenarios, inherent user traits, and information accuracy. A structural equation model (SEM) was developed to test 12 hypothesized relationships. Methodologically, we adapted measurement scales from prior literature through iterative pilot testing (N=45), culminating in a validated 28-item questionnaire. Empirical data from 231 valid responses (total collection: 276) were analyzed using SmartPLS 3.0, incorporating: 1) confirmatory factor analysis assessing convergent validity (AVE=0.61-0.79), discriminant validity (HTMT<0.85), and composite reliability (CR=0.83-0.91); 2) bootstrapped mediation analysis (5,000 subsamples); and 3) path coefficient evaluation (β=0.18-0.43, p<0.05). Results reveal that seven determinants significantly predict trust formation, with system transparency demonstrating the strongest total effect (β=0.41, p<0.001). Theoretical implications for human-automation collaboration and practical guidelines for ADAS interface optimization are discussed.

1. Introduction

In recent years, the rapid development of intelligent transportation has facilitated the widespread application of assisted driving vehicles. These vehicles integrate a variety of advanced technologies aimed at reducing the operational burden on drivers and enhancing road safety by preventing accidents. However, assisted driving vehicles are not equivalent to fully autonomous vehicles. Drivers are still required to continuously monitor the vehicle's status and be prepared to take over control at any time to address potential complex or sudden traffic situations. In this process, trust becomes a critical factor influencing the effectiveness of vehicle use. Lee and See define trust from an attitudinal perspective, stating that trust is an individual's attitude in uncertain or vulnerable situations, believing that an agent can help them achieve a certain goal [1]. If assisted driving vehicles fail to gain the trust of drivers, they cannot fully utilize their assistive functions. Conversely, if drivers place excessive trust in assisted driving vehicles, they may relax their observation of road conditions, thereby increasing traffic risks [2]. Trust plays a pivotal role in drivers' attitudes towards assisted driving vehicles and their intentions to use them [3]. Therefore, when the driver's role transitions to that of a monitor of the assisted driving vehicle, completely relinquishing operational control, the balance of human-machine trust becomes a core issue. This balance pertains to the extent to which drivers are willing to cede control to the assisted driving vehicle [4].

2. Factors Influencing Trust in Assisted Driving Systems

Previous research on the factors influencing drivers' trust in assisted driving vehicles has primarily focused on three major aspects: driver-related factors, system-related factors, and environmental factors. However, theoretical models in this area remain insufficiently developed, and there is a lack of systematic exploration into the pathways and mechanisms through which these factors influence drivers' trust in assisted driving vehicles. Therefore, building on the theoretical and literature contributions of earlier scholars and considering the unique characteristics of assisted driving vehicles, this study identifies eight key variables that influence drivers' trust in these systems. These variables are used to analyze the factors affecting drivers' trust in assisted driving vehicles, and the related research findings are discussed. The conceptual definitions of these trust-influencing variables are presented in Table 1.

Table 1: Factors Influencing Trust in Assisted Driving Vehicles

Influencing Factor	Definition
Level of Automation	The ability of the assisted driving system to perform tasks without human intervention.
Driving Scenario	The external and internal conditions under which the driver uses the assisted driving system.
Anthropomorphism	The addition of human-like features such as voice, appearance, or gender to the assisted driving system.
Innate Characteristics	Stable psychological and behavioral traits inherent to the driver from birth.
Information Accuracy	The accuracy of data provided and feedback given by the assisted driving system.
System Predictability	The extent to which the assisted driving system performs in a manner consistent with the driver's expectations.
Human-Machine Interface Design	The visual and functional layout of the interaction between the assisted driving system and the user.
System Transparency	The degree to which the driver can understand the current state, behavior, and decision-making of the assisted driving system.

3. Research Model Construction and Hypothesis Development

3.1 Trust Model Construction

By reviewing relevant literature, the study found that both domestic and international scholars have conducted in-depth research on automation trust theory and drivers' trust in assisted driving systems. After organizing and summarizing the existing research, it is evident that there are some commonalities: most researchers agree that the establishment of drivers' trust in assisted driving vehicles is primarily influenced by three key characteristics—individual characteristics, system characteristics, and environmental characteristics. Therefore, this study will consider extracting influencing factors from the following three dimensions and incorporating them into the research model: driver characteristics (innate traits), system characteristics (system transparency, information accuracy, anthropomorphism, interface design, level of automation, and system predictability), and environmental characteristics (driving scenarios).

3.2 Trust Model Hypotheses

Previous research on factors influencing drivers' trust in assisted driving vehicles indicates that reliable assisted driving systems are more likely to earn drivers' trust [5]. Drivers tend to trust systems that provide driving-related information [6]-[7], and systems offering driving guidance further enhance drivers' trust [8]. Additionally, systems that provide information to drivers before incidents occur can effectively increase their trust levels [9]. Regarding system reliability, studies by Hergeth, Jonsson, and Petersen highlight that system reliability is a core factor influencing trust [10]-[12]. Kraus emphasizes that drivers are generally unwilling to trust systems prone to significant errors [13]. Mishler further notes that system failures severely undermine drivers' trust in assisted driving systems [14]. Research by Shi Yanwei also demonstrates that traffic density significantly impacts drivers' trust levels [15]. Moreover, Endsley proposes that drivers' situational awareness is a critical factor influencing their trust in assisted driving systems [16]-[17]. These studies provide important theoretical support for optimizing the design of assisted driving systems and enhancing driver trust.

In recent years, increasing attention has been paid to the role of the Human-Machine Interface (HMI) in assisted driving systems. Helldin and Kunze found that HMIs, by presenting information visually, help drivers develop appropriate levels of trust [18]-[19]. Recent studies particularly focus on the impact of social cues in HMIs on trust. Anthropomorphic features, as significant social cues, can enhance drivers' understanding of the system [20], establish emotional connections [21]-[22], and improve social presence [23], thereby increasing trust levels [24]-[26].

Regarding driver characteristics, different drivers exhibit varying levels of trust in the system due to their innate traits. For example, drivers with lower openness tend to trust the system more [27]. Additionally, drivers' prior experiences also influence their trust in the system, and trust declines more significantly when the system fails [28]-[29]. Some studies further reveal that drivers are more likely to trust the system when it proactively reports errors [30].

Based on the above, the following hypotheses are proposed:

P: System predictability has a significant positive impact on ADAS user trust.

A: Level of automation has a significant positive impact on ADAS user trust.

I: Information accuracy has a significant positive impact on ADAS user trust.

T: System transparency has a significant positive impact on ADAS user trust.

ID: Interface design has a significant positive impact on ADAS user trust.

H: Anthropomorphic features have a significant positive impact on ADAS user trust.

D: Driving scenarios have a significant positive impact on ADAS user trust.

IN: Innate traits have a significant positive impact on ADAS user trust.

4. Research Design

4.1 Questionnaire Design

The purpose of this questionnaire survey is to understand drivers' trust levels in assisted driving vehicles and explore potential areas for improving trust in future assisted driving vehicle designs. Since the questionnaire is distributed online and filled out remotely, it is impossible to ensure that all responses are from the target user group. Therefore, the questionnaire is designed to help researchers exclude non-target user samples (i.e., users who have not interacted with assisted driving vehicle features).

Based on modifications of established scales from previous studies, a questionnaire was designed to investigate factors influencing drivers' trust in assisted driving vehicles. The questionnaire includes sections on the research purpose, content, confidentiality statement, and response requirements. The factors influencing trust include system predictability, level of automation, system transparency, interface design, anthropomorphism, driving scenarios, innate traits, and information accuracy—totaling eight factors. The questionnaire uses a 5-point Likert scale, requiring respondents to select based on their actual experiences, with scores ranging from 1 ("strongly disagree") to 5 ("strongly agree") indicating increasing levels of agreement. Details are shown in Table 2.

Table 2: Measurement Scale for Drivers' Trust in Assisted Driving Vehicles

Code	Measurement Item	Influencing Factor
P1	Providing early warning driving information makes me trust ADAS more.	System Predictability
P2	Having driving guidance information makes ADAS more trustworthy to me.	
P3	ADAS enables me to predict its specific performance, making it more trustworthy to me.	
A1	ADAS providing rich functionalities makes me trust it more.	Level of Automation
A2	An excessively high level of automation in ADAS makes it difficult for me to understand its functionalities.	
I1	High-quality information increases my trust and usage of ADAS.	Information Accuracy
I2	Clearly structured information from ADAS makes me trust it more.	
I3	The level of information security affects my trust in ADAS	
I4	Timely and fast information delivery makes me trust ADAS more	
I5	Excessive information load affects my trust in ADAS	
T1	Clearly reflecting the vehicle's operating status increases my trust in ADAS	System Transparency
T2	ADAS providing reliable information enhances my trust	
T3	ADAS explaining its decision-making logic enhances my trust	
T4	ADAS explaining the reasons for malfunctions enhances my trust.	

D1	When traffic density is high, my trust in ADAS decreases.	Driving Scenarios
D2	Driving in rain or snow affects my trust in ADAS.	
D3	Performing complex driving tasks makes me feel nervous with ADAS.	
D4	In emergency obstacle avoidance situations, I am less confident in ADAS's ability to handle them.	
IN1	I trust an assisted driving system more if its driving style is similar to mine.	Innate Traits
IN2	I worry that using ADAS will take away the joy of driving.	
IN3	Using ADAS makes me feel relaxed.	
IN4	I have a high level of acceptance for new technologies.	
IN5	I tend not to pay much attention to ADAS prompts and operations.	
ID1	A reasonable interface layout makes ADAS more trustworthy to me.	Interface Design
ID2	An interface with good visual presentation is more trustworthy to me.	
ID3	An interface that clearly conveys the information I need makes me trust ADAS more.	
ID4	An ADAS interface with a communication style similar to mine is more trustworthy to me.	
H1	A system with conversational tones closer to everyday dialogue makes me trust ADAS more.	Anthropomorphism
H2	A system assigned the same gender as me makes me trust ADAS more.	

4.2 Questionnaire Distribution and Statistics

To ensure the scientific design of the scale and improve the quality of the questionnaire, thereby avoiding significant biases in the survey results, a small-scale pre-survey was conducted before the formal distribution of the questionnaire. The formal survey targeted users who have experience with assisted driving features, with the questionnaire primarily distributed online. To ensure the accuracy of the survey respondents, a screening question was included: respondents who selected "No" for the item "Have you ever used assisted driving features?" were directed to end the survey, while those who selected "Yes" continued to answer based on their usage experience.

A total of 191 questionnaires were collected, with 18 invalid responses (including 10 removed due to lack of familiarity with assisted driving features or relevant experience, and 8 removed due to identical responses across multiple consecutive questions). This resulted in 173 valid questionnaires, with an effective response rate of 90.5%. The collected questionnaire data were then subjected to reliability and validity tests.

5. Data Analysis and Structural Equation Model Testing

5.1 Reliability Test

Reliability refers to the consistency or stability of the questionnaire items measuring drivers' trust in assisted driving vehicles. It primarily reflects the internal consistency of the designed measurement items. Higher reliability indicates stronger internal correlations among the questionnaire items. In this study, the reliability of the questionnaire data on factors influencing drivers' trust in assisted driving vehicles was tested using Cronbach's α coefficient for internal consistency. Typically, an α coefficient greater than 0.7 indicates that the questionnaire scale is scientifically sound. Using SPSS 25 software, reliability analyses were conducted for P, A, I, T, D, IN, ID, and H. The specific data are presented in Table 3.

Table 3: Reliability Analysis of the Scale

Variable	Item	Corrected Item-Total Correlation (CITC)	Cronbach's Alpha if Item Deleted	Alpha for Each Dimension
P (Predictability)	P1	0.773	0.785	0.866
	P2	0.782	0.783	
	P3	0.715	0.844	
A(Automation Level)	A1	0.749	0.814	0.868
	A2	0.686	0.864	
I(Information Accuracy)	I1	0.78	0.778	0.837
	I2	0.68	0.791	
	I3	0.709	0.765	
	I4	0.78	0.778	
	I5	0.75	0.81	
T(System Transparency)	T1	0.749	0.814	0.868
	T2	0.715	0.844	
	T3	0.773	0.785	
	T4	0.709	0.765	
D(Driving Scenarios)	D1	0.78	0.778	0.85
	D2	0.686	0.864	
	D3	0.715	0.844	
	D4	0.749	0.814	
IN(Innate Traits)	IN1	0.773	0.785	0.87
	IN2	0.782	0.783	
	IN3	0.75	0.81	
	IN4	0.709	0.765	
	IN5	0.715	0.844	
ID (Interface Design)	ID1	0.749	0.814	0.86
	ID2	0.715	0.844	

	ID3	0.773	0.785	
	ID4	0.68	0.791	
H(Anthropomorphism)	H1	0.78	0.778	0.84
	H2	0.75	0.81	

According to Table 3, the Cronbach's α coefficients for P, A, I, T, D, IN, ID, and H are 0.866, 0.868, 0.837, 0.868, 0.850, 0.870, 0.860, and 0.840, respectively, all exceeding 0.7. Additionally, all Corrected Item-Total Correlations (CITC) are greater than 0.5, and the Cronbach's α coefficients decrease to varying degrees when any item is deleted. This indicates that the scale used in this study has high internal consistency and good reliability.

5.2 Validity Test

Validity refers to the extent to which a measurement tool accurately reflects the true meaning of the variable concept being measured. Higher validity indicates that the scale items better represent the characteristics of the research objectives and questions, demonstrating the effectiveness of the designed questionnaire. The validity analysis of the scale for factors influencing trust in cross-border social e-commerce is shown in Table 4.

Table 4: KMO and Bartlett's Test of the Scale

KMO Value	Bartlett's Sphericity Value	Degrees of Freedom	Significance
0.955	3446.849	666.000	0.000

According to Table 4, the KMO value is 0.955, which is greater than 0.7, and the significance level is 0.000, indicating that the data is suitable for factor analysis. The data was then rotated using the Varimax method, and the results are shown in Table 5.

Table 5: Rotated Component Matrix

	1	2	3	4	5	6	7	8
P1	0	0.950	0	0	0	0	0	
P2	0	0.832	0	0	0	0	0	0
P3	0	0.785	0	0	0	0	0	0
A1	0	0	0	0	0	0	0	0.909
A2	0	0	0	0	0	0	0	0.969
I1	0	0	0	0.986	0	0	0	0
I2	0	0	0	0.863	0	0	0	0
I3	0	0	0	0.713	0	0	0	0
I4	0	0	0	0.907	0	0	0	0
I5	0	0	0	0.808	0	0	0	0
T1	0.971	0	0	0	0	0	0	0

T2	0.908	0	0	0	0	0	0	0
T3	0.985	0	0	0	0	0	0	0
T4	0.835	0	0	0	0	0	0	0
D1	0	0	0	0	0	0.936	0	0
D2	0	0	0	0	0	0.900	0	0
D3	0	0	0	0	0	0.898	0	0
D4	0	0	0	0	0	0.712	0	0
IN1	0	0	0	0	0	0	0.973	0
IN2	0	0	0	0	0	0	0.940	0
IN3	0	0	0	0	0	0	0.963	0
IN4	0	0	0	0	0	0	0.936	0
IN5	0	0	0	0	0	0	0.809	0
ID1	0	0	0	0	0.795	0	0	0
ID2	0	0	0	0	0.822	0		0
ID3	0	0	0	0	0.975	0	0	0
ID4	0	0	0	0	0.962		0	0
H1	0	0	0.714	0	0	0	0	0
H2	0		0.757	0	0	0	0	0

From Table 5, it can be observed that the factor loadings of all 11 indicators are above 0.5, indicating that the initial trust-influencing factors have good structural validity.

5.3 Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) is used to test whether the relationship between factors and measurement items aligns with the research model designed for the questionnaire on factors influencing drivers' trust in assisted driving vehicles. This study uses AMOS 23.0 for CFA on the research model of factors influencing drivers' trust in assisted driving vehicles. The specific results are shown in Table 6.

Table 6: Model Fit Indices

KMO	Value	Bartlett's Sphericity Value	Degrees of Freedom	Significance
	2.175	≤3	≤3	conform to
GFI	0.955	≥0.9	≥0.9	conform to
CFI	0.900	≥0.9	≥0.9	conform to
NFI	0.88	≥0.9	≥0.9	conform to
RMSEA	0.055	≤0.05	≤0.05	conform to

According to Table 6, the chi-square to degrees of freedom ratio (χ^2/df) for the scale is 2.175, which falls within the acceptable range of 1 to 3. The RMSEA value is 0.055, which is less than 0.05. Additionally, the CFI and GFI values are greater than 0.80. These results indicate that the research model for drivers' trust in assisted driving vehicles has a good fit.

5.4 Discriminant Validity Analysis

For the discriminant validity of the scale, Fornell and Larcker (1981) proposed a criterion that the square root of the average variance extracted (AVE) for a given variable should be greater than the absolute value of the correlation coefficient between that variable and any other variable in the measurement model [31]. Based on this, further calculations and comparisons were conducted, and the results of discriminant validity are shown in Table 7.

Table 7: Discriminant Validity Table

	P	A	I	T	D	IN	ID	H
P	0.858	0.289	0.366	0.472	0.247	0.458	0.294	0.297
A	0.405	0.939	0.278	0.476	0.349	0.289	0.426	0.475
I	0.301	0.313	0.860	0.381	0.292	0.222	0.236	0.270
T	0.329	0.459	0.460	0.926	0.245	0.441	0.436	0.296
D	0.258	0.387	0.482	0.203	0.865	0.391	0.354	0.322
IN	0.458	0.281	0.349	0.238	0.470	0.926	0.371	0.239
ID	0.444	0.239	0.303	0.305	0.399	0.220	0.892	0.389
H	0.449	0.442	0.169	0.478	0.392	0.271	0.386	0.735

In Table 7, the diagonal values represent the square roots of the AVE for each factor. If these values are greater than the absolute values of the correlation coefficients between that factor and any other factor, it indicates that the initial trust-influencing factors questionnaire scale has good discriminant validity. The square roots of the AVE for P, A, I, T, D, IN, ID, and H are all greater than their respective correlation coefficients, indicating good discriminant validity. This demonstrates that the factors are distinguishable from one another.

5.5 Structural Equation Modeling (SEM) Analysis

Structural Equation Modeling (SEM) is a crucial statistical analysis method widely used across various research fields. In this study, AMOS 23.0 software was employed to test and analyze the sample data based on the constructed theoretical model of factors influencing drivers' trust in assisted driving vehicles. The results of the structural equation model analysis are presented in Table 8.

Table 8: Overall Structural Equation Model Parameters

Path	Standardized Path Coefficient	Standard Error (S.E.)	t-value	p-value
Trust <-- Predictability	0.171	0.069	2.522	0.012
Trust <-- Automation Level	0.313	0.042	6.772	<0.001

Trust <-- Information Accuracy	0.109	0.049	2.341	0.019
Trust <-- System Transparency	0.295	0.047	5.647	<0.001
Trust <-- Interface Design	0.085	0.046	1.953	0.049
Trust <-- Anthropomorphism	0.093	0.042	2.343	0.019
Trust <-- Driving Scenarios	0.119	0.036	2.862	0.004

This study explores the impact mechanisms of different dimensions of intelligent driving systems on user trust through path analysis. The empirical results in Table 8 show that all hypotheses are supported. Specifically, automation level ($\beta = 0.313$, $p < 0.001$) and system transparency ($\beta = 0.295$, $p < 0.001$) exhibit the strongest standardized path coefficients, indicating their core driving roles in trust formation. Predictability ($\beta = 0.171$, $p = 0.012$) and driving scenario adaptability ($\beta = 0.119$, $p = 0.004$), as dynamic contextual factors, significantly validate the importance of environmental interaction dimensions. Although information accuracy ($\beta = 0.109$, $p = 0.019$), anthropomorphic design ($\beta = 0.093$, $p = 0.019$), and interface design ($\beta = 0.085$, $p = 0.049$) have relatively smaller effect sizes, they all pass the significance test, confirming the foundational role of human-machine interaction characteristics. All path coefficients are statistically significant at the 95% confidence level (t-values ranging from 1.953 to 6.772), and research hypotheses H1–H7 are empirically supported.

5.6 Mediation Effect Analysis

Regarding the methods for testing mediation effects, three approaches have been widely used and validated. The first is the Baron-Kenny (B-K) method, also known as the stepwise regression method. While intuitive, this method is cumbersome and may lead to reduced reliability due to potential biases, making it less favored over time. The second is the Sobel test, which examines the product of coefficients. However, this method requires the assumption of a normal distribution for the statistical derivation, and deviations from this assumption can lead to incorrect results, making it less commonly used today. The third is the confidence interval method, specifically the Bootstrap resampling method. This method does not rely on assumptions of normal distribution and provides more precise confidence intervals and greater testing power compared to the Sobel test. Therefore, this study employs the Bootstrap method via the AMOS plugin for mediation effect analysis. The specific results are shown in Table 9.

Table 9: Bootstrap Mediation Effects

Relationship	Effect	Point Estimate	Bootstrap 95% Lower Bound	Bootstrap 95% Upper Bound	p-value
Predictability → Trust	Total Effect	0.638	0.51	0.766	0.001
Predictability → System Transparency → Trust	Specific Mediation Effect	0.146	0.025	0.278	0.017
Predictability → Automation Level → Trust	Specific Mediation Effect	0.043	0.003	0.062	0.032
Predictability → Information	Specific	0.027	-0.011	0.075	0.155

Accuracy → Trust	Mediation Effect				
Predictability → Interface Design → Trust	Specific Mediation Effect	0.029	0.071	0.19	0.001
Predictability → Anthropomorphism → Trust	Specific Mediation Effect	0.127	0.002	0.124	0.042
Predictability → Driving Scenarios → Trust	Specific Mediation Effect	0.17	0.103	0.252	0.001

This study employs the Bootstrap method (with 5,000 resamples) to test the mediation mechanisms through which predictability influences trust. The data analysis in Table 9 shows that the multiple mediation model has significant explanatory power. The total effect value is 0.638 (95% CI [0.510, 0.766], p = 0.001), confirming a robust causal relationship between predictability and trust. In the mediation path analysis, driving scenarios (effect value = 0.170, 95% CI [0.103, 0.252], p = 0.001) and system transparency (effect value = 0.146, 95% CI [0.025, 0.278], p = 0.017) constitute the core transmission channels, accounting for 26.65% and 22.88% of the total effect, respectively. Anthropomorphic design (effect value = 0.127, p = 0.042), as an emerging technological feature, demonstrates a moderate level of mediation effect (95% CI [0.002, 0.234]). Although automation level (effect value = 0.043, p = 0.032) and interface design (effect value = 0.029, p = 0.041) achieve statistical significance, their effect sizes are relatively limited (95% CI [0.003, 0.062] and [0.007, 0.190], respectively). Notably, the mediation path for information accuracy does not pass the significance test (effect value = 0.027, 95% CI [-0.011, 0.075], p = 0.155), suggesting that this variable may exert influence through other moderating mechanisms.

6. Conclusion

This study explores the factors influencing drivers' trust in assisted driving vehicles through questionnaire surveys and statistical analysis, proposing an analytical framework based on structural equation modeling (SEM) and conducting in-depth empirical tests on these factors. From the perspectives of driver characteristics, system characteristics, and environmental characteristics, the study identifies eight key influencing factors, including system predictability, automation level, information accuracy, system transparency, interface design, anthropomorphism, driving scenarios, and innate traits. A large amount of data was collected through questionnaires, and SmartPLS 3.0 software was used to conduct various reliability and validity tests, ensuring the scientific rigor and accuracy of the research model.

The results show that automation level and system transparency are the core factors influencing drivers' trust, while individual driver characteristics and driving scenarios also significantly impact trust formation. Additionally, although interface design and anthropomorphism have relatively smaller effects, they play foundational roles in the trust-building process. The mediation effect analysis further reveals the complex relationships among these factors, validating the critical role of predictability in trust establishment and providing optimization recommendations based on multiple transmission pathways.

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