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Article

Research on Development Decision-Making for Shared Autonomous Vehicles Based on Social Media Data Mining

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Abstract

The successful deployment of shared autonomous vehicle (SAV) technologies is of great significance for improving road traffic safety and road capacity. Nevertheless, the practical implementation of SAV technologies is hindered by ambiguous user acceptance intentions and complicated multi-stakeholder decision-making processes. Existing studies mostly conduct static analyses of user willingness with fragmented variable selection, lacking integrated frameworks that integrate public opinion mining, behavioral modeling, and evolutionary game theory. Different from existing studies that predominantly rely on static questionnaire-based willingness analysis with subjectively selected variables, this study integrates social-media text mining, an extended Theory of Planned Behavior, and a tripartite evolutionary game model to jointly investigate user psychological mechanisms and multi-stakeholder dynamic interactions. To explore the long-term development trajectory of SAVs, this study crawls 23,943 short-video comment datasets. The Latent Dirichlet Allocation (LDA) topic model is adopted to preliminarily identify eight core factors affecting users' adoption of SAVs, based on which a questionnaire survey on SAV adoption intention is designed. A total of 724 valid questionnaires were collected. Expanding the classic Theory of Planned Behavior (TPB), this study incorporates additional latent variables including perceived risk, employment impacts, and government attitudes to construct an extended TPB model, which quantifies the correlations between latent constructs and adoption intention. The empirical results reveal that government attitudes ($\beta = 0.497$, $p < 0.001$) and employment conditions ($\beta = 0.434$, $p < 0.001$) exert significantly positive effects on perceived risk. Perceived ease of use indirectly determines adoption intention through three mediating paths: attitude toward behavior, subjective norm, and perceived behavioral control. Furthermore, stakeholders are categorized into three groups (users, enterprises, and governments), and a tripartite evolutionary game model for SAV stakeholders is established to derive evolutionary stable strategies (ESS) via numerical simulation. The simulation results indicate that the strategy combination of economic incentives and small-scale pilot programs (adopted by governments) paired with the adoption strategy (adopted by potential SAV users) constitutes the evolutionary stable strategy. Variations in governments' economic incentive costs and small-scale pilot operation costs significantly alter the decision-making behaviors of potential SAV users. This study integrates behavioral modeling and game-theoretic analysis. It delivers theoretical foundations for research on SAV adoption behaviors and provides quantitative decision-making evidence for governments to formulate phased incentive policies and for service platforms to control pilot operation costs.

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1. Introduction

The sharing economy has become a research focus in recent years. It improves the efficiency of resource use and promotes fair access to social resources. Shared mobility is a key component of the sharing economy. It allows users to access transportation services when needed [1], thus maximizing the utilization of mobility resources [2]. According to the Survey Data on China's Shared Mobility Market Overview and User Travel Behaviors in 2025 [3], shared car services can reduce car ownership, ease traffic congestion, and lower emissions [4]. These services also reduce travel costs and make trips more convenient.

At the same time, the World Automobile Organization reports that there are 1.446 billion cars in use worldwide [5], with nearly 90 million new cars added each year. This dramatic expansion of vehicle quantities has given rise to a host of social dilemmas and challenges, among which the frequent occurrence of road traffic accidents stands as the most severe one. Autonomous driving technology has been rapidly deployed in recent years as a viable solution to such issues. According to data from the U.S. National Highway Traffic Safety Administration (NHTSA), the number of incident reports associated with autonomous vehicles (AVs) and advanced driver assistance systems (ADAS) surged from 329 in 2021 to 1384 in 2024, and further climbed to approximately 2230 in 2025, marking a year-on-year increase of 57%. Notably, mature Level 4 (L4) autonomous driving systems deliver superior safety performance per traveled mile relative to human drivers. Public data from Waymo demonstrates that its robotaxi fleet has accumulated over 35 million operational miles, recording merely 0.09 injury claims per million miles—an approximately 95% reduction compared with the human driver baseline of 1.09 injury claims per million miles [6]. Existing scholarly studies confirm that autonomous vehicles can not only improve road safety, but also enhance travel comfort, cut travel expenses, and generate significant socioeconomic benefits [7].

The intersection of the sharing economy and transportation has therefore attracted growing academic interest. With the development of autonomous driving, shared autonomous vehicles (SAVs) have emerged as a new concept. SAVs combine the features of shared cars and autonomous vehicles. They offer potential advantages in traffic safety, transportation efficiency, and reducing the number of private cars [8]. From the perspective of industrial practice, robotaxis are transitioning from technical verification to large-scale commercial operation. By the end of 2025, the total number of service orders completed throughout the year reached 12.86 million, and the number of covered cities expanded to 38 [9]. Market forecasts also remain optimistic. Research by Goldman Sachs predicts that the global robotaxi market size will reach approximately 415 billion US dollars by 2035, while Morgan Stanley projects that this sector will evolve into a trillion-dollar mobility gateway by 2040 [10].

Nevertheless, in stark contrast to the rapidly expanding industrial scale and bullish market outlooks, substantial uncertainty persists regarding public acceptance of autonomous driving. The existing literature demonstrates that public adoption of autonomous driving technologies is not determined solely by technical performance; instead, it is jointly shaped by multi-dimensional factors including perceived risk, trust, perceived usefulness, social norms, and psychological empowerment. Among these factors, safety concerns are widely recognized as the primary barrier to public acceptance: perceived risk exerts a significant negative effect on adoption intention, whereas trust and perceived benefits serve as positive driving forces. Cross-national comparative studies further reveal notable disparities in public acceptance intentions across countries and cultural contexts [11], alongside considerable fluctuations in trust and acceptance levels even within identical demographic groups [12,13]. Notably, in regions with ongoing shared autonomous vehicle (SAV) pilot programs, public trust does not rise linearly alongside technology deployment. Several studies have even documented declining user trust and optimism toward such mobility services. Such uncertainty and heterogeneity in public acceptance indicate that user behavioral intention acts as a core constraint hindering the large-scale commercial rollout of shared autonomous vehicles. Accordingly, investigating user behavioral intention toward shared autonomous vehicles carries profound theoretical and practical implications, and facilitates the advancement of intelligent transportation systems.

Accordingly, this study conducts text mining on TikTok comment data. Taking cleaned and processed web-scraped data and questionnaire survey data as fundamental datasets, this research develops the Latent Dirichlet Allocation (LDA) topic model and partial least squares structural equation modeling (PLS-SEM) to explore travel intentions and their influencing factors among early adopters of shared autonomous vehicles (SAVs). Furthermore, this paper investigates the group evolutionary behaviors of three game stakeholders—governments, SAV operating platforms, and potential SAV users—in the development process of SAVs, establishes a tripartite dynamic evolutionary game model, and discusses a series of practical issues arising after the commercial launch of SAV services.

This study makes three main contributions to the existing literature on shared autonomous vehicles. From a methodological perspective, this research identifies users' genuine concerns via social media comment text mining, which guides the configuration of latent variables for the extended Theory of Planned Behavior (TPB). This approach addresses the drawbacks of conventional questionnaire-based studies, where variable selection tends to be subjective and fragmented. From a theoretical perspective, two understudied external social factors—employment conditions and government attitudes—are incorporated into the analytical framework of user adoption intention, which further reveals the transmission mechanism through which external contexts shape public risk perceptions and travel willingness. From a practical perspective, the tripartite evolutionary game model covering governments, service platforms and users is constructed to identify critical threshold values of core cost parameters, providing quantitative decision-making references for the phased pilot promotion and deployment of SAVs.

2. Literature Review

2.1. Shared Autonomous Vehicles (SAV)

In recent years, the public has put forward higher requirements for the quality of transportation services, and per capita travel demand has continued to rise. However, prominent contradictions have emerged between operational efficiency and environmental carrying capacity in the existing urban transportation system: issues such as traffic congestion, environmental pollution, persistently high carbon emissions, and the "last-mile" travel dilemma not only severely restrict residents' travel efficiency but also pose challenges to urban ecology and sustainable development [14]. Against this background, exploring new shared transportation modes has become a core issue in the future development of urban transportation [15]. As an important component of the future urban transportation system, shared mobility has the potential to alleviate the pain points of urban transportation, yet its actual effectiveness and impacts remain widely controversial. Proponents argue that shared mobility can effectively reduce reliance on private cars, ease traffic congestion, cut pollution, and improve overall travel efficiency; critics, however, point out that the sharing model is prone to triggering new problems: for example, the random parking of shared

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bikes occupies public space and poses safety hazards, while shared mobility modes such as ride-hailing may exacerbate local congestion and lead to an uneven distribution of service supply [16].

As a landmark technological breakthrough in the field of artificial intelligence, autonomous driving is a key direction for future transportation transformation. It significantly weakens the constraints of age and physical conditions on motorized travel, making independent travel possible for the elderly, unlicensed individuals, and minors [17]. At present, autonomous vehicles have been able to stably achieve autonomous driving in simple scenarios such as highways; with continuous technological iteration, their applications are gradually expanding to more complex scenarios, including urban mixed-traffic roads, rural roads, and complex weather conditions.

Shared autonomous driving is the in-depth integration of shared transportation modes and autonomous driving technology. It can not only significantly improve transportation operational efficiency, alleviate energy and environmental pressures, and reduce residents' travel costs but also profoundly reshape the characteristics of road traffic flow and residents' travel behavior, exerting far-reaching impacts on urban infrastructure layout, spatial structure, and land use [18,19]. Therefore, it is urgent to construct a strategic framework for shared autonomous driving oriented toward long-term development.

2.2. Influencing Factors of Autonomous Driving Car Selection

Existing research highlights two major categories of determinants: objective attributes and psychological latent variables.

For objective attributes, most studies focus on socio-economic and travel-related characteristics. Hohenberger [7] showed that men are more likely than women to adopt autonomous vehicles. Bansal [8,20] and Webb [21] reported that high-income and highly educated groups are more willing to use this technology. Haboucha [22] noted that elderly people prefer conventional private cars, while Lavieri [23] found that residents with higher education are more likely to be early adopters. Travel attributes also play a significant role. Krueger et al. [24], in their study in Australia, identified cost, travel time, and waiting time as key variables. Winter [25] expanded this to include walking time, in-vehicle time, and search time. Zhu [26] showed that perceived value of time is positively related to willingness to use, while perceived risk is negatively related.

Second, in terms of psychological latent variables, passengers' perceived safety inside shared autonomous vehicles (SAVs) serves as the threshold for acceptance [13]. Prevailing concerns over technical reliability, cybersecurity and data privacy constitute the primary barriers to adoption. Notably, recent autonomous driving research has moved beyond basic analyses of adoption intention, and begun to elaborate human–machine interaction mechanisms from multiple dimensions including safety evaluation, hazardous situation recognition, user emotion and trust analysis, and decision-making drivers, all of which directly shape user's perceived risks and attitudes toward SAVs [11].

In the dimension of safety evaluation and hazardous situation recognition, vision-language models can detect high-risk driving behaviors such as sudden cut-ins and aggressive lane changes in real time and generate risk inference results. Their recognition accuracy and response speed lay the technical foundation for users' sense of safety. For user emotion and trust analysis, vision-language assistants such as the Keep Yelling Assistant (KYA) identify dangerous driving scenarios via YOLOv8 and leverage large language models to produce emotional responses tailored to driver preferences [27]. Relevant findings demonstrate the vital role of emotional interaction in user experience and trust formation for autonomous vehicles. From the perspective of decision-making drivers, end-to-end vision-language-action (VLA) models such as DriveMoE implement dynamic decision-making through a mixture-of-experts architecture with scene-specific and skill-specific specialization [28]. The transparency and interpretability of such decisions directly govern users' judgment of system competence and their trust levels.

Against this backdrop, conventional adoption studies remain predominantly centered on static psychological constructs. Mohammad [21] incorporated personal innovativeness, data privacy concerns and price sensitivity as predictors of usage intention. Lee [22] investigated determinants of autonomous vehicle adoption by examining latent variables including perceived ease of use, perceived usefulness, behavioral intention, perceived risk, relative advantage, self-efficacy and psychological ownership. Empirical evidence collected in the Netherlands by Yap [23] indicates that trust and sustainability exert positive effects on adoption intention, whereas driving enjoyment hinders user uptake. Kaur et al. [24] highlighted the significance of performance expectancy and system reliability. Nazari [25] further demonstrated that green travel tendencies and demand-responsive mobility substantially improve acceptance of shared mobility modes, while perceived safety risks act as a core inhibiting factor.

Overall, the existing literature has systematically identified determinants of user adoption intention from two layers: objective vehicle/service attributes and partial psychological latent variables. Nevertheless, most studies rely on static analytical frameworks and fail to fully account for the dynamic evolution of user behaviors. Accordingly, scholars have increasingly adopted dynamic modeling tools such as game theory to unpack travel choice mechanisms under multi-stakeholder interactions.

2.3. The Application of Evolutionary Game Theory in Transportation

Building on the above, scholars have shifted from static analysis to dynamic interaction. Evolutionary game theory has become an important tool to explain the evolution of travel behavior.

Liu [29] developed a framework based on game theory and innovation utility, providing dynamic allocation strategies for congestion management. Maryam [30] proposed a spatial game model to assess the effects of urban policies on the competition between public and private transport. Zhang [31] introduced a logit evolutionary game model to explain the dynamics between shared and private cars. He suggested that governments can encourage shifts to shared cars by raising the costs of private car use, such as fuel, insurance, and parking fees. Peng [32] further constructed a four-party evolutionary game involving government, platforms, drivers, and passengers, and analyzed the policy impacts on each party. Mo et al. constructed a tripartite evolutionary game model involving governments, automobile manufacturers, and consumers to investigate consumers' purchase intention toward private autonomous vehicles. They adopted parameter perturbation simulations to characterize the dynamic impacts of regulatory policies and corporate R&D investment [12].

In summary, research in this field increasingly emphasizes multi-party interaction. Yet, few studies examine user choices regarding shared autonomous vehicles or the related industry-level games.

2.4. Review of Literature Review

Overall, abundant research achievements have been accumulated regarding behavioral intentions toward autonomous vehicles. Most existing studies focus on objective variables such as socioeconomic characteristics and travel attributes, and predominantly center on user behavior analyses covering adoption intention surveys, service platform optimization, pricing strategy formulation, and policy recommendations. Although several studies have attempted to incorporate psychological latent variables, they suffer from fragmented and insufficiently justified variable selection. The modeling of user willingness largely relies on theoretically preset variables without support from real public opinion data, and questionnaire-based empirical analyses are dominated by static approaches that overlook the impacts of external social factors including employment shocks and government policies. By identifying variable themes through media data mining, the present study evaluates the factors shaping adoption intentions for shared autonomous vehicles (SAVs) in a more objective manner.

Furthermore, the prior literature fails to uncover the dynamic evolutionary laws of user choice behaviors and neglects to analyze the effects of external variables such as government supervision and strategic interactions among operating platforms. This study integrates a complete analytical pipeline consisting of text mining and PLS-SEM; this study also explores the dynamic evolution laws of shared autonomous vehicle services, aiming to provide theoretical support for formulating systematic development strategies.

3. Data Collection and LDA

3.1. Social Media Data Mining

3.1.1. Data Collection

Among short-video platforms, TikTok stands as a highly representative carrier, with over 900 million daily active users. It boasts a large, highly active and demographically diversified user base. Users who post comments under relevant autonomous driving videos generally hold a certain degree of interest in the technology and can be regarded as potential adopters of shared autonomous vehicles (SAVs) in the future. In line with the research objectives of this study, one-week observation windows are adopted to capture users' real-time attitudes and perceptions toward relevant events, thereby laying a solid and reliable foundation for subsequent analysis. The detailed data collection procedures are specified as follows.

First, topic searches are conducted on TikTok using a set of keywords including "Hangzhou", "driverless vehicles", "shared autonomous vehicles", and "Apollo Go". The screening criteria for eligible videos are defined as follows: (1) video content is directly relevant to shared autonomous vehicles; (2) the video has at least 10,000 likes and no fewer than 500 comments; and (3) the release date falls within three months prior to the data collection date.

Videos are sorted comprehensively by release time and popularity. After removing irrelevant clips, a final sample of 16 valid videos is retained. A web crawler is then deployed to extract five categories of metadata, namely video ID, comment text, comment ID, comment likes, and comment reply counts, yielding an initial dataset consisting of 23,943 raw comment records.

For comment filtering, only publicly available text-based comments are preserved, whereas meaningless entries such as pure emojis, image-only posts, and texts with fewer than five characters are discarded. To improve the precision of downstream analytical outputs, a multi-stage data preprocessing pipeline is implemented: (1) Deduplication: Fully duplicate comments are eliminated through dual matching of unique comment IDs and full comment text content; (2) Filtering of promotional content: Advertising, marketing and official promotional comments are screened out via keyword matching supplemented by manual inspection; (3) Chinese word segmentation: The jieba segmentation tool is utilized to split Chinese comment texts under the precise segmentation mode; (4) Stop-word removal: Two stop-word lexicons are applied, including the Harbin Institute of Technology stop-word list (767 stop words) and a self-defined supplementary list containing modal particles, internet slang and semantically empty vocabulary.

Comments posted merely to reach character quotas or irrelevant to shared autonomous vehicles are further eliminated in the preprocessing stage. After all cleaning procedures, a refined dataset of 21,421 valid comment records is obtained for subsequent modeling.

3.1.2. Theme Feature Extraction and Naming

The Latent Dirichlet Allocation (LDA) model can mine latent topics embedded in texts and quantify the associations between topics and vocabularies, exhibiting strong practicability. Taking preprocessed comment texts about shared autonomous vehicles (SAVs) as input, this study constructs an LDA topic model using the Gensim 4.3.3 library in Python 3.12 to identify relevant latent topics.

Perplexity is a core indicator for evaluating LDA model performance [33]. It measures the model's ability to predict unseen documents; a sudden increase in perplexity indicates that the model begins to overfit and the extracted topics become fragmented. In this study, the number of candidate topics is restricted to the range of 1 to 10, consistent with the horizontal axis of Figure 1, and the maximum number of training iterations is set to 50. The model is trained repeatedly to analyze the variation trend of perplexity derived from comment data. As shown in Figure 1, the perplexity curve exhibits a clear elbow point at K = 8. When K is less than or equal to 8, the perplexity increases gradually and smoothly, indicating that each additional topic still contributes effectively to capturing distinct public concerns. However, when K exceeds 8, the perplexity rises sharply. This abrupt increase indicates that beyond 8 topics, newly added topics begin to overlap semantically with existing topics, leading to topic fragmentation and model overfitting. In addition to the elbow-point criterion from the perplexity curve, manual interpretability screening further confirms K = 8 as the optimal choice: at K = 8, each of the eight topics corresponds to a semantically distinct and practically interpretable public concern (e.g., safety risk, employment impact, policy attitude, perceived ease of use, behavioral attitude, subjective norm, perceived behavioral control, and behavioral intention); when K exceeds 8, some extracted themes become semantically redundant and cannot be independently named with clear real-world meaning. Therefore, the optimal number of extracted topics is determined as eight (K = 8). The trend curve of model perplexity is illustrated in Figure 1.

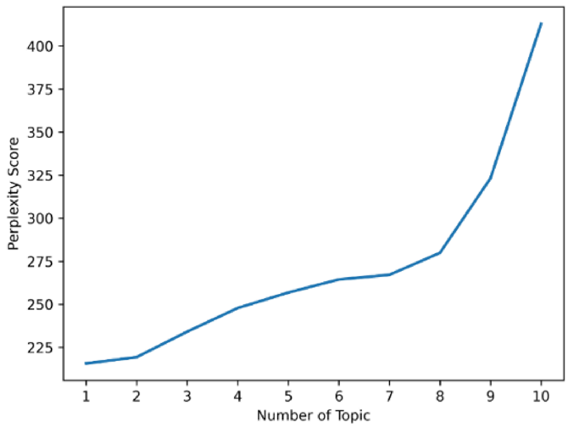

Figure 1. Comment on the trend in confusion.

The LDA model outputs the corresponding keywords under each of the eight topics, which are sorted in descending order of topic weight. The keywords extracted after LDA modeling in this research are listed in Table 1.

Table 1. Keywords of LDA model.

Serial Number	Keywords
1	Autonomous driving; will not (exclude); want to (expect); feel; possible (neutral); cheap;
2	Driverless; promotion; trial; discussion; machine; care
3	Driving; unmanned driving; accident; insurance; night; incident; traffic police; safety
4	In the future; no need; to take a driving test; driving license; drinking; driving school; experience
5	Autonomous driving; steering wheel; smooth; wipers; avoid; future; significance
6	Issues; technology; dare not; in the future; intelligent; robots; development; traffic accidents
7	Driver; unemployment; autonomous driving; taxi; laid off; ride-hailing; safety; Didi
8	Government; attitude; support; risk; opposition; driverless

From Table 1, two main observations can be made:

(1) Keywords such as "driver" and "unemployment" appear frequently. This indicates that shared autonomous vehicles may significantly affect the occupational structure. It also reflects public concerns about changes in employment patterns and the potential risks to social stability brought by technological progress.

(2) Safety emerges as another prominent theme. While the public generally accepts that technological progress is inevitable, concerns about safety remain evident.

Based on the themes extracted through LDA and guided by the Theory of Planned Behavior, the topics are categorized and named as follows: Behavioral Attitude, Subjective Norm, Perceived Risk, Perceived Ease of Use, Perceived Behavioral Control, Behavioral Intention, Employment Risk, and Policy Impact [13,34]. The LDA themes and associated keywords are presented in Table 2.

Table 2. LDA topic words.

Subject Term	Keywords
Behavioral attitude	Autonomous driving; will not (exclude); want (expect); feel; possible (neutral); cheap;
Subjective norms	Driverless; promotion; trial; discussion; machine; care
Perceiving risk	Driving; unmanned driving; accident; insurance; night; incident; traffic police; safety
Easy to perceive	In the future; no need; to take a driving test; driving license; drinking; driving school; experience
Perceived behavioral control	Autonomous driving; steering wheel; smooth; windshield wipers; avoidance; future; significance
Behavioral intention	Issues; technology; dare not; in the future; intelligent; robots; development; traffic accidents
Employment situation	Driver; unemployment; autonomous driving; taxi; laid off; ride-hailing; safety; Didi
Policy Impact	Government; attitude; support; risk; opposition; driverless

The following content will refer to the above theme words to design an extended Theory of Planned Behavior model for the research on the behavioral intention of shared autonomous driving.

3.2. Conceptual Research Model and Hypotheses Development

3.2.1. Employment Situation

The rise of shared autonomous vehicles has created uncertainty for ride-hailing and taxi drivers. Their labor rights are poorly defined, social security coverage is limited, and incomes have become unstable due to technological change and market competition. This group therefore faces an uncertain future [35].

H1. *Employment situation affects the perceived risk of travelers choosing shared autonomous vehicles [35,36].*

3.2.2. Government Attitude

Government policies play an important role in shaping users' choices. Supportive measures such as subsidies or discounts can increase perceptions of cost-effectiveness. Stronger regulation of operators can also enhance confidence in service safety and quality, encouraging adoption. Conversely, restrictive measures such as traffic controls or operating limits can reduce convenience and discourage use.

H2. *Government attitude affects the perceived risk of travelers choosing shared autonomous vehicles [37,38].*

3.2.3. Perceived Risk

Perceived risk is a key factor in consumer decision-making. It is multidimensional, covering financial, functional, social, psychological, and physical aspects [39,40]. Among these, safety is the most critical factor in the adoption of shared autonomous vehicles [41].

H3. *Perceived risk affects the perceived ease of use of travelers choosing shared autonomous vehicles [42,43].*

3.2.4. Perceived Ease of Use

Perceived ease of use directly shapes behavioral attitudes and intentions [42]. Mathieson emphasized the match between consumer abilities and the skills required to use new technologies. This construct is closely related to Ajzen's concept of perceived behavioral control. When evaluating emerging technologies, ease of use is a key positive predictor of attitudes.

H4. *Perceived ease of use affects behavioral attitude [44].*

H5. *Perceived ease of use affects subjective norm [45].*

H6. *Perceived ease of use affects perceived behavioral control [46].*

3.2.5. Behavioral Attitude

Behavioral attitude refers to an individual's overall evaluation of a specific behavior. It is a strong antecedent of behavioral intention.

H7. *Behavioral attitude affects behavioral intention [45].*

3.2.6. Subjective Norm

Subjective norm captures perceived social pressure from others regarding behavior. Individual decisions are often shaped by expectations of peers or reference groups.

H8. *Subjective norm affects behavioral intention [47].*

3.2.7. Perceived Behavioral Control

Perceived behavioral control reflects the extent to which individuals feel they have the resources and opportunities to perform a behavior. A lack of enabling conditions reduces willingness to adopt new technologies. It is thus a core determinant of behavioral intention.

H9. *Perceived behavioral control affects behavioral intention.*

3.2.8. Construct Model

Drawing on the above analysis, this study constructs a structural model with user travel intention as the outcome variable. The model incorporates employment situation, government attitude, perceived risk, perceived ease of use, behavioral attitude, subjective norm, and perceived behavioral control. It examines how these factors influence user intention and the mechanisms underlying their effects. Given that Partial Least Squares Structural Equation Modeling (PLS-SEM) can effectively handle measurement errors and is suitable for exploratory research [48], it is adopted as the analytical method. The structural model is shown in Figure 2.

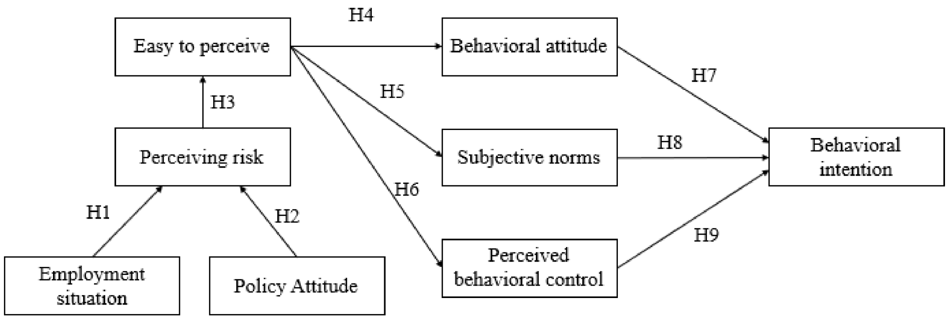

Figure 2. Extended Theory of Planned Behavior Model.

4. Method

This section addresses three components: experimental design, data collection, and data measurement validation.

4.1. Experimental Design

For specific variable measurement, a five-point Likert scale was adopted, where scores ranging from 1 to 5 correspond to "completely inconsistent" to "completely consistent", respectively. Respondents were instructed to select a score based on the statements of scale items and their own degree of agreement.

To ensure the reliability and validity of the study's measurement instruments, corresponding observed variables were selected for the latent variables examined—including employment status, government attitude, perceived risk, perceived ease of use, behavioral attitude, subjective norm, and perceived behavioral control—and relevant measurement models were established.

The study's questionnaire was developed by: (1) analyzing the existing literature, (2) drawing on validated scales from prior scholars, and (3) considering the attributes of potential shared autonomous vehicle (SAV) users. A pre-survey was administered to potential SAV users; subsequent data analysis was conducted to evaluate the questionnaire's operability and feasibility. The scale was revised based on these pre-survey results to further ensure its reliability and validity. The revised latent variable measurement scale is presented in Table 3.

Table 3. Revised Measurement Scale for Latent Variables.

Latent Variable	Encoding	Scale Question
Government attitude	PO1	If government agencies formulate policies to encourage the development of the shared autonomous vehicle industry, I would use shared autonomous vehicles for transportation.
	PO2	If the government departments effectively manage the operational prices of the shared autonomous vehicle industry, I would use shared autonomous vehicles for travel.
	PO3	If government departments effectively manage the qualifications of shared autonomous vehicle travel service platforms, I would use shared autonomous vehicle travel.
Employment situation	EC1	I believe that when shared autonomous vehicles are put on the market, it will decrease the demand in the labor market.
	EC2	I believe that when shared autonomous vehicles enter the market, they will have a certain impact on the ride-hailing and taxi industries.
	EC3	I believe that when shared autonomous vehicles are launched in the market, they will undermine the management efficiency of the existing industry.
Behavioral attitude	At1	I believe that using shared autonomous vehicles will be enjoyable and fun once they are put on the market.
	At2	Compared to traditional ride-hailing services, I trust shared autonomous vehicles more.
	At3	Once shared autonomous vehicles are put on the market, I believe that shared autonomous vehicles should be strongly promoted.
Subjective norms	SN1	My friends and relatives will support me in using shared autonomous vehicles.
	SN2	The attitudes and opinions of people around me towards shared autonomous vehicles will affect my use of shared self-driving cars.
	SN3	The attitudes of my relatives and friends towards shared driverless cars will influence my use of shared autonomous vehicles.
Perceived behavioral control	PBC1	Once shared autonomous vehicles are launched in the market, I can use shared self-driving cars as long as I want.
	PBC2	Once shared self-driving cars are put on the market, it will be easy to learn how to operate shared autonomous vehicles.
	PBC3	Once shared self-driving cars are on the market, it will be my own decision whether to use shared self-driving cars for travel.
Behavioral intention	BI1	When shared autonomous cars are launched in the market, I plan to use shared autonomous cars.
	BI2	When shared self-driving cars are put on the market, I will try to use shared self-driving cars as much as possible.
	BI3	When shared self-driving cars are put on the market, I will prioritize using shared self-driving cars.
Perceiving risk	PR1	I am concerned that shared autonomous vehicles will be more prone to device or system failures.
	PR2	I worry that shared autonomous vehicles will make my travel privacy more easily exposed.
	PR3	I am worried that the improper operation of shared autonomous vehicles will threaten my personal safety.

Table 3. *Cont.*

Latent Variable	Encoding	Scale Question
Easy perceive	PE1	I believe that operating shared self-driving cars is more convenient than traditional cars.
	PE2	I think shared self-driving cars are easy to operate and use.
	PE3	I believe I can quickly master the process of using shared self-driving cars.

4.2. Data Collection

The formal online questionnaire survey was conducted from June to July 2024. Target respondents were Chinese members of the public with basic awareness or interest in shared autonomous vehicles. Questionnaires were distributed via snowball sampling on social-network platforms including WeChat, QQ and Weibo. A screening question was placed at the beginning to filter out respondents who had no basic understanding of shared autonomous vehicles. After data collection, data cleaning was performed: questionnaires with response duration shorter than 90 s, straight-lining answers, and logically contradictory responses were removed. A total of 817 questionnaires were collected; after validity screening, 724 valid samples were retained, yielding an effective response rate of 88.6%. The survey was fully anonymous. Informed consent was obtained from each participant. No personal identifiable information such as name or phone number was collected; only demographic information and travel-attitude items were recorded. Sample descriptive statistics are shown in Table 4.

Table 4. Descriptive Statistical Analysis of the Sample.

Variable	Option	Proportion (%)
Gender	Male	51.7
	Female	48.3
Age	0–14 years old	5.7
	15–25 years old	22.4
	26–45 years old	47.5
	46–60 years old	21.4
	61 years old and above	3
Level of education	Junior high school and below	25.7
	High school or vocational school	33.4
	Undergraduate or college diploma	33.6
	Master's degree or above	7.3
Disposable personal income	Below 2000 yuan	26.6
	2000–5000 yuan	25.6
	5001–8000 yuan	17.1
	8001–10,000 yuan	27.8
	Above 10,000 yuan	2.9
Employment situation	Students in school	7.9
	employees of enterprises and institutions	21.1
	Individual entrepreneur	26.5
	freelancer	23.1
	Online car-hailing drivers and taxi drivers	16.7
	Other	4.7

5. Measurement Model

5.1. Reliability and Validity Analysis

Using SPSS 24.0 software, the collected raw data was input into the software to analyze the reliability and validity of the questionnaire. Regarding reliability, in this study, the evaluation of the scale's reliability was primarily conducted through measuring item internal consistency. Internal consistency was verified by the composite reliability (rho_c) value and Cronbach's alpha coefficient. In exploratory research, a composite reliability (rho_c) value above 0.7 and a Cronbach's alpha coefficient greater than 0.6 are required [49]. According to the reliability statistics of the scale, the reliability coefficient of government attitude is 0.867, the reliability coefficient of employment situation is 0.859, the reliability coefficient of attitude is 0.872, the reliability coefficient of subjective norms is 0.891, the reliability coefficient of perceived behavioral control is 0.873, the reliability coefficient of behavioral intention is 0.874, the reliability coefficient of perceived risk is 0.873, and the reliability coefficient of perceived ease of use is 0.852. The reliability of this questionnaire meets the requirements. For validity, this paper used exploratory factor analysis to analyze whether each observed variable has stable consistency, employing SPSS software to examine the composition of each dimension. KMO values and Bartlett's test of sphericity results were used for validity analysis. The evaluation criteria are: KMO value greater than 0.7 and a significance of less than 0.05 for Bartlett's test. If the questionnaire results meet these two criteria, this indicates that the observed variables have a strong correlation, suitable for factor analysis. According to the exploratory factor analysis results of the scale, the KMO value of this questionnaire is 0.993, and the corresponding significance in Bartlett's test of sphericity is 0.000 < 0.05, indicating that the scales have good validity, as shown in Table 5:

Table 5. Reliability and convergent validity statistics of measurement items.

Variable	Factor Loadings	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)	CR
PO1 PO2 PO3	0.871 0.894 0.902	0.872	0.873	0.921	0.796	0.9188
EC1 EC2 EC3	0.869 0.892 0.888	0.874	0.875	0.923	0.799	0.914
At1 At2 At3	0.889 0.892 0.897	0.859	0.859	0.914	0.78	0.9217
SN1 SN2 SN3	0.914 0.912 0.892	0.871	0.872	0.921	0.795	0.9322
PBC1 PBC2 PBC3	0.906 0.881 0.888	0.852	0.854	0.91	0.772	0.9209
BI1 BI2 BI3	0.904 0.877 0.9	0.867	0.87	0.919	0.79	0.9225
PR1 PR2 PR3	0.908 0.878 0.893	0.873	0.874	0.922	0.797	0.922

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Table 5. *Cont.*

Variable	Factor Loadings	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)	CR
PE1 PE2 PE3	0.887 0.862 0.886	0.891	0.892	0.933	0.822	0.9102

In addition, this study verifies the discriminant validity of the scale using the Fornell–Larcker criterion. According to classical test theory, the average variance extracted (AVE) values are all greater than 0.5, meeting the standard for convergent validity, and the composite reliability (CR) values are all above the critical threshold of 0.7, indicating that each dimension of the scale has good internal consistency reliability. The rationale is that it quantifies the explanatory power of specific latent variables over their observed indicators' variance. In structural equation modeling, when the square root of the AVE for all latent variables is significantly higher than the correlation coefficients between that variable and other constructs, it can be confirmed that the measurement model has good discriminant validity, as shown in Table 6.

Table 6. Discriminant validity results (Fornell–Larcker criterion).

	AT	BI	EC	PBC	PE	PO	PR	SN
AT	0.892							
BI	0.870	0.894						
EC	0.858	0.858	0.883					
PBC	0.869	0.873	0.875	0.892				
PE	0.855	0.857	0.852	0.862	0.879			
PO	0.867	0.875	0.868	0.863	0.851	0.889		
PR	0.864	0.861	0.865	0.872	0.856	0.873	0.893	
SN	0.875	0.878	0.870	0.867	0.863	0.870	0.870	0.906

The results of the discriminant validity test indicate that the square roots of the AVE for all latent variables (bold values on the diagonal) are greater than their correlations with other latent variables (non-diagonal values), ensuring that the measurement model of the study is scientific and reliable.

5.2. Model Testing

This section will elaborate on model testing and model data analysis. Structural model testing primarily refers to testing the model's fit and checking for multicollinearity; model data analysis mainly includes the path coefficients and *p*-value tests between various hypotheses. In this study, the model fit evaluation is conducted using the Standardized Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI). According to the criteria set by Hu and Bentler [50], when the SRMR is less than 0.08, it indicates good model fit; when SRMR is less than 0.10, it indicates acceptable model fit; and when SRMR is greater than 0.10, it means the model fit is poor and requires further inspection and improvement. The Normed Fit Index measures the discrepancy between observed data and the model's predicted values, providing information about the goodness of fit of the model. The range of the NFI values is from 0 to 1; generally speaking, the closer the NFI value is to 1, the better the model fit. According to the table below, the SRMR value of the model proposed in this study is 0.113, slightly higher than 0.1, and the NFI value is 0.893, very close to 0.9. However, PLS focuses on prediction-oriented outcomes and does not enforce perfect global fit, making it more common for it to have an SRMR slightly above 0.1 compared to covariance structure models. The academic community is generally more lenient with the SRMR threshold for PLS. For this exploratory study, the model has acceptable predictive performance and also meets the requirements. Therefore, it can be determined that the model basically satisfies the fit. The model fit results are shown in Table 7.

Table 7. Model Fit Capability Assessment.

	Saturated Model	Estimated Model
SRMR	0.035	0.113
d_ULS	0.358	3.802
d_G	0.477	0.863
Chi-square	1905.697	2740.253
NFI	0.893	0.845

When there is a high correlation between the observed variables in a measurement model, collinearity problems will arise. This situation can lead to an increase in the standard errors of the indicator weights, thereby causing biases in the sign and value of the estimates [51]. Before performing model analysis, it is necessary to test for collinearity between factors. The VIF values in this study range from 1.964 to 2.817, and the variance inflation factor values are below 5, indicating that the model does not have severe collinearity issues and can be used for structural model analysis, as shown in Table 8 below.

Table 8. Collinearity assessment (VIF).

Variable	VIF
AT1	2.292
AT2	2.339
AT3	2336
BI1	2.560
BI2	2.135
BI3	2.467
EC1	2.005
EC2	2.282
EC3	2.268
PBC1	2.528
PBC2	2.208
PBC3	2.256
PE1	2.156
PE2	1.964
PE3	2.204
PO1	2.097
PO2	2.347

Table 8. *Cont.*

Variable	VIF
PO3	2.403
PR1	2.566
PR2	2.175
PR3	2.341
SN1	2.817
SN2	2.776
SN3	2.395

5.3. Path Analysis

The bootstrap method has advantages in handling complex models, non-ideal data conditions, and improving the accuracy of statistical tests during path result analysis [52,53]; at the same time, the bootstrap method can generate empirical distributions through resampling when analyzing structural equation models, without the need to preset data distribution forms. Therefore, this paper uses the bootstrap method to analyze the structural model, setting the number of subsamples to 5000, with the results shown in Table 9.

Table 9. PLS-SEM path coefficient, t-statistics, *p*-values and hypothesis test outcomes.

Path	Path Coefficient	Student's *t* Test	*p*-Value	Test Results
Behavioral attitude ≥ Behavioral intention	0.283	7.627	0.000	Accept
Employment situation ≥ Perceived risk	0.434	11.103	0.000	Accept
Perceived behavioral control ≥ Behavioral intention	0.322	9.185	0.000	Accept
Perceived ease of use ≥ Behavioral attitude	0.855	71.996	0.000	Accept
Perceived ease of use ≥ Perceived behavioral control	0.862	75.422	0.000	Accept
Perceived ease of use ≥ Subjective norm	0.863	74.844	0.000	Accept
Government attitude ≥ Perceived risk	0.497	13.186	0.000	Accept
Perceived risk ≥ Perceived ease of use	0.856	70.471	0.000	Accept
Subjective norms ≥ Behavioral intention	0.352	9.086	0.000	Accept

Table 9 illustrates that all latent variables exert a significant positive effect on overall behavioral intention, with *p*-values less than 0.001 and t-statistics greater than 1.96. The results indicate that government attitude (β = 0.497, t = 13.186) and employment situation (β = 0.434, t = 11.103) are closely associated with perceived risk, respectively. Subsequently, perceived risk (β = 0.856, t = 70.471) significantly positively affects perceived ease of use. In turn, perceived ease of use has significant positive impacts on behavioral attitude (β = 0.855, t = 71.996), perceived behavioral control (β = 0.862, t = 75.422), and subjective norm (β = 0.863, t = 74.844). Ultimately, behavioral intention is positively predicted by three factors: behavioral attitude (β = 0.283, t = 7.627), perceived behavioral control (β = 0.322, t = 9.185), and subjective norm (β = 0.352, t = 9.086). Among these predictors of behavioral intention, subjective norm stands as the most influential factor, followed by perceived behavioral control and then behavioral attitude.

The latent variables above can be categorized into three stakeholders from a subject perspective: individual users, service companies providing shared autonomous vehicles, and governments responsible for traffic governance.

From the perspective of individual users, when making travel decisions, they not only select travel services offered by enterprises but also receive guidance and incentives from governments. Government actions further shape individuals' behavioral attitude, perceived ease of use, perceived risk and other perceptions.

From the corporate perspective, enterprises should vigorously promote shared autonomous vehicles to capture market share while cutting operational and administrative costs [54]. They also need to explore approaches to fully satisfy users' diverse travel demands, deliver high-quality shared mobility services to users [55], and establish unified market standards and transparent technical specifications, which in turn affect the public's subjective norms and perceived behavioral control.

From the government's perspective, holistic governance is required. In the development of shared autonomous mobility, governments ought to safeguard users' legitimate rights and interests, and provide effective guidance for the operation and innovation of shared autonomous vehicles [56,57].

On this basis, the following section conducts an in-depth discussion based on the tripartite game among users, enterprises and governments.

6. Evolutionary Game Model

6.1. Basic Assumptions

Based on the previous analysis of the participants in shared autonomous vehicles, the following assumptions are made for the model:

Assumption 1. *The government, the platform for shared autonomous vehicle usage, and potential users of shared autonomous vehicles represent three different game groups, all of whom are boundedly rational individuals.*

Assumption 2. *Promoting the operation and management of shared autonomous vehicles through multi-party collaboration can enhance the social credibility of the government, bringing corresponding economic benefits.*

Assumption 3. *The government can choose to adopt two strategies, guiding incentives or economic incentives; the operation of shared autonomous vehicles can adopt two behavioral strategies, small-scale pilot operation and large-scale promotion operation; and potential users of shared autonomous vehicles can choose two strategies, support for small-scale pilot shared autonomous vehicles and opposition to small-scale pilot shared autonomous vehicles.*

Assumption 4. *The probability that the government adopts the economic incentive strategy is x, and the probability that it adopts the guiding incentive strategy is $1 - x$, where $0 \leq x \leq 1$; the probability that shared autonomous vehicles choose small-scale pilot operation is y, and the probability that they choose large-scale promotion operation is $1 - y$, where $0 \leq y \leq 1$; and the probability that potential users support small-scale pilot shared autonomous vehicles is z, while the probability that they oppose small-scale pilot shared autonomous vehicles is $1 - z$, where $0 \leq z \leq 1$.*

6.2. Construction of Evolutionary Game Model

(1) Three-Party Evolutionary Game Model. Based on the above analysis, eight strategic combinations are obtained for the government, shared autonomous vehicle platforms, and potential users of shared autonomous vehicles. Based on this, a three-party game

tree for the operation of shared autonomous vehicles is constructed, as shown in Figure 3.

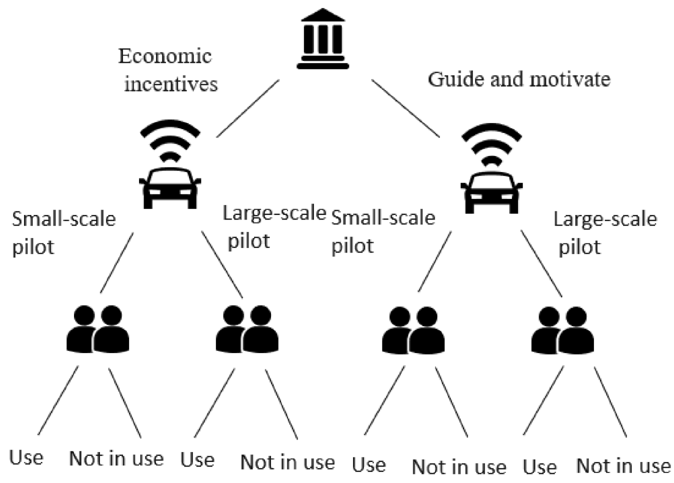

Figure 3. Three-Party Game Tree for Shared Autonomous Vehicles.

(2) Revenue Matrix Construction. The relevant parameters for the game subjects are shown in Table 10.

Table 10. Definition of parameters for the tripartite evolutionary-game model.

Parameter	Meaning
x	The probability that the government chooses to formulate economic incentive strategies.
y	The probability of choosing a small-scale pilot operation strategy for shared autonomous vehicles.
z	The potential users of shared autonomous vehicles support the likelihood of a small-scale pilot shared autonomous vehicle strategy.
Cg1	The government incurs costs when guiding, motivating, and sharing the operation of autonomous vehicles.
Cg2	The government incurs costs for the operation of shared autonomous vehicles through economic incentives.
Rg1	Government benefits from guiding and incentivizing small-scale pilot projects for shared autonomous vehicle companies.
Rg2	Economic incentives for government revenue during small-scale pilot programs of shared autonomous vehicle companies.
Rp1	When the government guides and incentivizes shared autonomous vehicles, there are additional benefits for the platform.
Rp2	When the government provides economic incentives for shared autonomous vehicles, the platform gains additional revenue.
Rp3	The shared autonomous vehicle platform chooses small-scale pilot benefits.
Cu1	The cost of using shared autonomous vehicles when users support small-scale pilots.
Cu2	The cost of using shared autonomous vehicles when users support large-scale promotion.
Ru1	The economic benefits of users choosing shared autonomous vehicles for travel under government economic incentives.
Ru2	The psychological benefits of users choosing shared autonomous car travel.

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Table 10. *Cont.*

Parameter	Meaning
Fp1	The government encourages the sharing of autonomous vehicle platforms without choosing small-scale pilot penalties.
Fp2	The government imposes fines for not choosing small-scale pilot studies for shared autonomous vehicle platforms under economic incentives.
Cp1	The additional costs of a shared autonomous vehicle platform when choosing small-scale pilot programs.

It can be inferred that there are eight combinations of game strategies among the government, shared autonomous vehicle platforms, and users: (economic incentives, small-scale pilot, usage), (economic incentives, large-scale pilot, usage), (economic incentives, small-scale pilot, no usage), (economic incentives, large-scale pilot, no usage), (guidance motivation, small-scale pilot, usage), (guiding motivation, large-scale pilots, usage), (guided motivation, small-scale pilot, no usage), and (guided motivation, large-scale pilot, no usage). The combined benefits of the strategy involving the government, the shared autonomous driving car platform, and users are shown in Table 11.

Table 11. The combined benefits of the three-party strategies.

Game Strategy	Government Revenue	Sharing the Revenue of Autonomous Driving Car Platforms	User Earnings
Economic incentives, small-scale pilot, usage	−Cg2 + Rg2	Cg2 + Rp2 + Rp3 − Cp1	Ru1 + Ru2 − Cu1
Economic incentives, large-scale pilot, usage	−Cg2 + Fp2	−Fp2	Ru1 + Ru2 − Cu2
Economic incentives, small-scale pilot, no usage	−Cg2 + Rg2	Cg2 − Cp1	0
Economic incentives, large-scale pilot, no usage	−Cg2	Rp3 − Fp2	0
Guidance motivation, small-scale pilot, usage	−Cg1 + Rg1	Cg1 + Rp1 + Rp3 − Cp1	Ru2 − Cu1
Guiding motivation, large-scale pilots, usage	−Cg1 + Fp1	−Fp1	Ru2 − Cu2
Guided motivation, small-scale pilot, no usage	−Cg1 + Rg1	Cg1 − Cp1	0
Guided motivation, large-scale pilot, no usage	−Cg1	Rp3 − Fp1	0

Note: A value of "0" in the user earnings column indicates that users obtain zero net benefit when they select the "not-to-use" strategy for shared autonomous vehicles.

6.3. Analysis of Evolutionary Game Models

6.3.1. Construction of the Revenue Function

(1) Construction of the Government Revenue Function. Assuming the expected revenue from the government's implementation of 'economic incentives' and 'guiding incentives' is G11 and G12, based on the revenue in the table above:

$$G_{11} = y \times z \times \left(-C_{g2} + R_{g2}\right) + (1-y) \times z \times \left(-C_{g2} + F_{p2}\right) \\ +y \times (1-z) \times \left(-C_{g2} \times R_{g2}\right) + (1-y) \times (1-z) \times \left(-C_{g2}\right) \quad (1)$$

$$G_{12} = y \times z \times \left(-C_{g1} + R_{g1}\right) + (1-y) \times z \times \left(-C_{g1} + F_{p1}\right) \\ +y \times (1-z) \times \left(-C_{g1} \times R_{g1}\right) + (1-y) \times (1-z) \times \left(-C_{g1}\right) \quad (2)$$

According to the mathematical relationship between 'economic incentives' and 'guidance incentives', the average expected government revenue can be derived as follows:

This is example 2 of an equation:

$$G_{average} = x \times G_{11} + (1-x) \times G_{12} \quad (3)$$

(2) Construction of the revenue function for shared autonomous vehicle platforms: Let the expected revenues for the shared autonomous vehicle platform's 'small-scale pilot' and 'large-scale promotion' be P11 and P12, respectively, as shown in the table above.

$$P_{11} = x \times z \times \left(C_{g2} + R_{p2} + R_{p3} - C_{p1}\right) + (1-z) \times x \times \left(C_{g2} - C_{p1}\right) + z \times (1-x) \\ \times \left(C_{g1} + R_{p1} + R_{p3} - C_{p1}\right) + (1-x) \times (1-z) \times \left(C_{g1} - C_{p1}\right) \quad (4)$$

$$P_{12} = x \times z \times \left(-F_{p2}\right) + (1-z) \times x \times \left(R_{p3} - F_{p2}\right) + z \times (1-x) \\ \times \left(-F_{p1}\right) + (1-x) \times (1-z) \times \left(R_{p3} - F_{p1}\right) \quad (5)$$

According to the mathematical relationship between 'small-scale pilot' and 'large-scale promotion', the average expected revenue of shared driving cars can be obtained as follows:

$$P_{average} = y \times P_{11} + (1-y) \times P_{12} \quad (6)$$

(3) Let the expected benefits for the user implementing 'use' and 'not use' be U11 and U12, respectively. According to the above table of benefits, the following can be derived:

$$U_{11} = x \times y \times (R_{u1} + R_{u2} - C_{u1}) + (1-y) \times x \times (R_{u1} + R_{u2} - C_{u2}) + y \times (1-x) \times (R_{u2} - C_{u1}) \\ +(1-x) \times (1-y) \times (R_{u2} - C_{u2}) \quad (7)$$

$$U_{12} = x \times y \times 0 + (1-y) \times x \times 0 + y \times (1-x) \times 0 + (1-x) \times (1-y) \times 0 = 0 \quad (8)$$

According to the mathematical relationship between 'usage' and 'non-usage', the average expected user benefits can be derived as follows:

$$U_{average} = z \times U_{11} + (1-z) \times U_{12} \quad (9)$$

According to the Malthusian reproduction dynamic equation, the rate of change when the government implements economic incentives is as shown in the equation:

$$F(x) = \frac{d_x}{d_1} = x \times \left(G_{11} - G_{average}\right) = x \times (1-x) \times (G_{11} - G_{12}) \quad (10)$$

The rate of change for the large-scale promotion of shared autonomous vehicle companies is shown in the formula as follows:

$$F(y) = \frac{d_y}{d_1} = y \times \left(P_{11} - P_{average}\right) = y \times (1-y) \times (P_{11} - P_{12}) \quad (11)$$

The rate of change in users' travel when using shared autonomous vehicles is shown in the formula:

$$F(z) = \frac{d_z}{d_1} = z \times \left(U_{11} - U_{average}\right) = z \times (1 - z) \times (U_{11} - U_{12}) \tag{12}$$

In summary, by combining the above, we can derive the replication dynamic equation through the simultaneous equations.

$$\begin{cases} F(x) = x \times (1 - x) \times (C_{g1} - C_{g2} - F_{p1} \times z + F_{p2} \times z - R_{g1} \times y + R_{g2} \times y + F_{p1} \times y \times z - F_{p2} \times y \times z) \\ F(y) = y \times (1 - y) \times (C_{g1} - C_{p1} + F_{p1} - R_{p3} - C_{g1} \times x + C_{g2} \times x - F_{p1} \times x + F_{p2} \times x + R_{p1} \times z + 2 \times R_{p3} \times z - R_{p1} \times x \times z + R_{p2} \times x \times z) \\ F(z) = z \times (1 - z) \times (-C_{u2} + R_{u2} - C_{u1} \times y + C_{u2} \times y + R_{u1} \times x) \end{cases} \tag{13}$$

6.3.2. Model Result

According to the conclusions proposed by Ritzberger and Weibull [38], when solving the game strategies of the government, enterprises, and users, it is easy to identify eight special equilibrium points: E1 (0,0,0), E2 (1,0,0), E3 (0,1,0), E4 (0,0,1), E5 (1,1,0), E6 (1,0,1), E7 (0,1,1), and E8 (1,1,1). Existing research indicates that in asymmetric evolutionary game activities, if there is information asymmetry among multiple game subjects, then the asymptotic stable solution in the evolutionary game replication dynamic system must be a strictly Nash equilibrium solution [58]. Therefore, this paper only needs to discuss the stability of equilibrium points E1—E8. According to Lyapunov's stability theory [59], the Jacobian matrix can be obtained to derive the eigenvalues of the replication dynamic equations to analyze the stability of the local equilibrium points. Based on this theory, the Jacobian matrix for the evolutionary game in this paper is shown as formulated.

$$F = \begin{matrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{matrix} \tag{14}$$

Among them:

$$\begin{aligned} f_{11} = (1 - 2x) \times (C_{g1} - C_{g2} - F_{p1} \times z + F_{p2} \times z - R_{g1} \times y + R_{g2} \times y + F_{p1} \times z \times y - F_{p2} \times z \times y) F(z) = \tfrac{d_z}{d_1} \\ = z \times \left(U_{11} - U_{average}\right) = z \times (1 - z) \times (U_{11} - U_{12}) \end{aligned} \tag{1}$$

$$f_{12} = x \times (x - 1) \times \left(F_{p2} \times z - F_{p1} \times z + R_{g1} - R_{g2}\right) \tag{16}$$

$$f_{21} = y \times (y - 1) \times \left(C_{g1} - C_{g2} + F_{p1} - F_{p2} + R_{p1} \times z - R_{p2} \times z\right) \tag{17}$$

$$\begin{aligned} f_{22} = (1 - 2y) \times (C_{g1} - C_{p1} + F_{p1} - R_{p3} - C_{g1} \times x + C_{g2} \times x - F_{p1} \times x + F_{p2} \times x + R_{p1} \times z + 2 \times R_{p3} \times z \\ - R_{p1} \times x \times z + R_{p2} \times x \times z) \end{aligned} \tag{18}$$

$$f_{23} = y \times (1 - y) \times \left(R_{p1} + 2 \times R_{g3} - R_{p1} \times x + R_{p2} \times x\right) \tag{19}$$

$$f_{31} = z \times (1 - z) \times (R_{u1} + R_{u2} \times y) \tag{20}$$

$$f_{32} = z \times (z - 1) \times (C_{u1} - C_{u2} + R_{u2} - R_{u2} \times x) cc \tag{21}$$

$$f_{33} = (1 - 2 \times z) \times (C_{u1} - C_{u2} + R_{u2} - C_{u1} \times y + C_{u2} \times y + R_{u1} \times x - R_{u2} \times y + R_{u2} \times x \times y) \tag{22}$$

According to Lyapunov's first method for judging the local stability of each equilibrium point, when all the eigenvalues of the Jacobian matrix have negative real parts, it indicates that the equilibrium point is an evolutionarily stable strategy (ESS) of the system [56]; when at least one eigenvalue of the Jacobian matrix has a positive real part, this indicates that the equilibrium point is unstable. If there are eigenvalues with a real part equal to zero, and all other eigenvalues have negative real parts, it indicates that the stability of the equilibrium point cannot be judged by the sign of the eigenvalues, as shown in Table 12 below.

Table 12. Stability Analysis of the Equilibrium Point.

Balance Point	Stability Conditions			Stability
(0,0,0)	Cg1 − Cg2 < 0	Cg1 − Cp1 + Fp1 − Rp3 < 0	−Cu2 + Ru2 < 0	Condition 1
(1,0,0)	Cg2 − Cg1 < 0	Cg2 − Cp1 + Fp2 − Rp3 < 0	Ru1 − Cu2 + Ru2 < 0	Unstable point
(0,1,0)	Cg1 − Cg2 − Rg1 + Rp3 < 0	Cp1 − Cg1 − Fp1 + Rp3 < 0	Ru2 − Cu1 < 0	Condition 2
(0,0,1)	Cg1 − Cg2 − Fp1 + Fp2 < 0	Cg1 − Cp1 + Fp1 + Rp1 + Rp3 < 0	Cu2 − Ru2 < 0	Condition 3
(1,1,0)	Cg2 − Cg1 + Rg1 − Rg2 < 0	Cp1 − Cg2 − Fp2 + Rp3 < 0	Ru1 + Ru2 − Cu1 < 0	Condition 4
(1,0,1)	Cg2 − Cg1 + Fp1 − Fp2 < 0	Cg2 − Cp1 + Fp2 + Rp2 + Rp3 < 0	Cu2 − Ru1 − Ru2 < 0	Condition 5
(0,1,1)	Cg1 − Cg2 − Fp1 − Rp1 − Rp3 < 0	Cp1 − Cg1 − Fp1 − Rp1 − Rp3 < 0	Cu1 − Cu2 < 0	Condition 6
(1,1,1)	Cg2 − Cg1 + Rg1 − Rg2 < 0	Cp1 − Cg2 − Fp2 − Rp2 − Rp3 < 0	Cu1 − Ru1 − Ru2 < 0	Condition 7

Note on stability conditions: Condition 1 corresponds to equilibrium E1 (0,0,0), where all three parties adopt passive strategies (government guiding incentives, platform large-scale promotion, users not using); Condition 2 corresponds to E3 (0,1,0), where only the platform chooses small-scale pilot operation; Condition 3 corresponds to E4 (0,0,1), where only users choose to use SAV services; Condition 4 corresponds to E5 (1,1,0), where the government and platform adopt active strategies while users do not use; Condition 5 corresponds to E6 (1,0,1), where the government provides economic incentives and users adopt the service while the platform pursues large-scale promotion; Condition 6 corresponds to E7 (0,1,1), where the platform conducts small-scale pilots and users adopt the service while the government relies on guiding incentives; and Condition 7 corresponds to E8 (1,1,1), the ideal evolutionarily stable strategy where the government provides economic incentives, the platform conducts small-scale pilot operations, and users actively adopt SAV services. Each condition comprises three inequality constraints that must be simultaneously satisfied for the corresponding equilibrium point to be asymptotically stable.

From the table, it can be seen that since Cg2 − Cg1 < 0 cannot be satisfied, the equilibrium point E2 (1,0,0) does not meet the stability condition and is therefore an unstable point. The other equilibrium points E1 (0,0,0), E3 (0,1,0), E4 (0,0,1), E5 (1,1,0), E6 (1,0,1), E7 (0,1,1), and E8 (1,1,1) need to be evaluated based on relevant parameter values to determine if they meet the stability condition.

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6.4. Numerical Experiment and Simulation Analysis

6.4.1. Scenario Analysis of Evolutionary Results

The preceding text elucidated the strategic choices of three parties—the government, shared autonomous vehicle companies, and users—under different conditions through dynamic analysis and Jacobian matrix stability analysis. Due to the excessive number of parameters, MATLAB 9.12 software was used for model simulation. Through the aforementioned analysis of stable strategies, a stable equilibrium point that can evolve was obtained. The parameters were assigned values, and they were integrated into the pre-written program code along with the dynamic equations for numerical experiments. The initial proportions of "economic incentives, small-scale pilot, and usage" chosen by the government, shared autonomous vehicle companies, and users were set between 0 and 1. The x-axis, y-axis, and z-axis represent the proportions of government incentives, small-scale pilots chosen by shared autonomous vehicles, and user usage, respectively. To meet the interests of all parties while achieving an ideal equilibrium state in the game results, the initial parameter settings must conform to the evolutionary conditions $\lambda1 = Cg2 - Cg1\ Rg1 - Rg2 < 0$, $\lambda2 = Cp1 - Cg2 - Fp2 - Rp2 - Rp3 < 0$, and $\lambda3 = Cu1 - Ru1 - Ru2 < 0$. Assuming the parameter values are x = y = z = 0.5, and $t \in (0, 5)$, the following initial value settings are provided: Cg1 = 14.5, Cg2 = 15.5, Fp1 = 11, Fp2 = 13, Rg1 = 12, Cp1 = 15, Rp1 = 12, Rp2 = 10, Rp3 = 11, Cu2 = 17, Ru1 = 13, Ru2 = 11, Cu1 = 18, Rg2 = 17.

As shown in Figure 4, the evolutionary system among the government, shared autonomous vehicle companies, and potential users of shared autonomous vehicles has an evolutionary stability point at E8 (1,1,1), meaning that the strategy combination of the government, shared autonomous vehicle companies, and potential users (economic incentives, small-scale pilot tests, usage) is an evolutionarily stable strategy. It can be seen that this simulation analysis yields conclusions consistent with the stability analysis of the three-party evolutionary strategies, indicating that the model has a certain degree of validity.

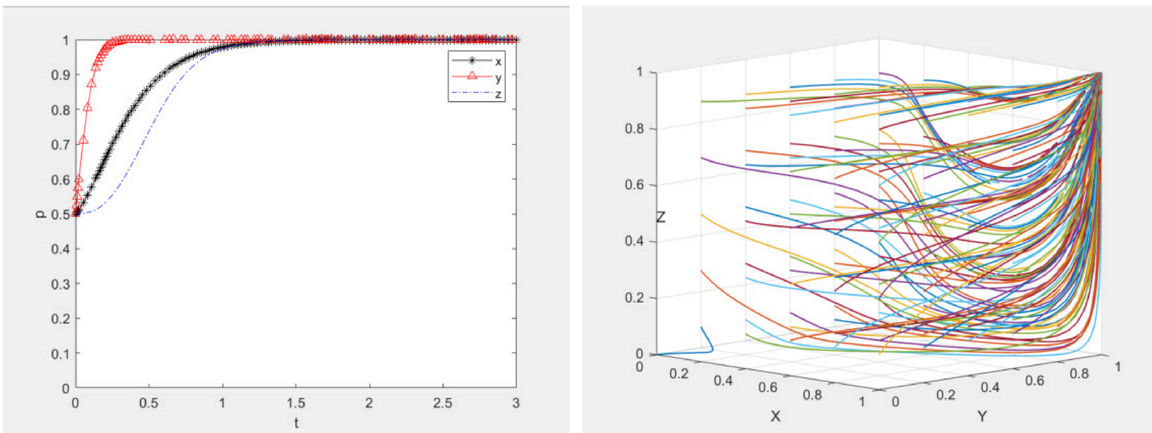

Figure 4. Evolutionary stability trends.

Based on the stable strategy combination, economic incentive costs and small-scale pilot costs are selected as evolutionary parameters to explore their impact on the game results.

6.4.2. The Influence of System Parameters on Evolutionary Stability Strategies

This section analyzes the impact of two parameters, the cost of economic incentives and the cost of small-scale pilot projects, on the results of system evolutionary games through numerical simulations. The impact of the government's economic incentive cost Cg2 for the shared autonomous vehicle platform on the evolutionary results. To reflect the government's implementation of economic subsidy behaviors on the incentive process for shared autonomous vehicle companies, we set the initial strategy choices for the government, shared autonomous vehicle companies, and potential users of shared autonomous vehicles as x = y = z = 0.3. Keeping other parameters unchanged, we vary the government's economic incentive levels for shared autonomous vehicle companies to Cg2 = 10, 15, and 20, representing low, medium, and high levels of government economic incentives, respectively. The simulation results are shown in Figure 5.

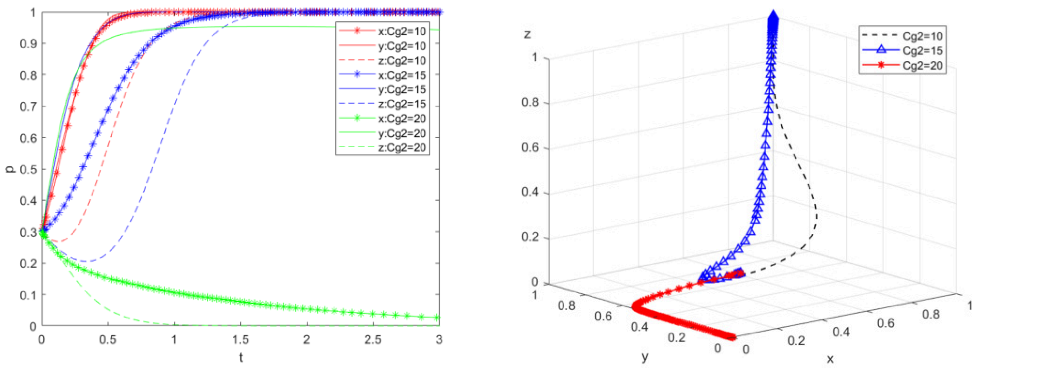

Figure 5. Evolution trajectories of a three-party game under different economic incentive costs.

It can be seen that the government's economic incentive cost Cg2 for shared autonomous vehicles has a critical value, which is between 15 and 20. When the government's economic incentive cost exceeds this critical value, the government will not choose to provide economic incentives to shared autonomous vehicle companies, and excessively high economic costs will also affect the travel choices of potential users of shared autonomous vehicles. At this time, the system's evolution stable point is (0,1,0). When the government's economic incentive cost is below this critical value, the probability of evolution in a positive direction among the government, shared autonomous vehicle companies, and potential users of shared autonomous vehicles increases. Users are more willing to use shared autonomous vehicles for travel, and companies will respond positively to government subsidies. The government's economic incentive cost will change the strategy choices of potential users of shared autonomous vehicles. When the government's economic incentive cost is too high, potential users will perceive the burden pressure of the government, thereby affecting their willingness to use. When the government's economic incentive cost is moderate, it will promote the system to evolve to the stable point E8 (1,1,1).

The impact of the shared autonomous vehicle platform's small-scale pilot cost Cp1 on evolution results. To reflect the impact of the small-scale pilot cost of the shared autonomous vehicle platform on the strategies of the three parties in the game, we set the initial strategy choices of the government, shared autonomous vehicle companies, and potential users as x = y = z = 0.3, while keeping other parameters unchanged. Let the shared autonomous vehicle companies adopt small-scale pilot costs, Cp1 = 15, 20, 25, representing low, medium, and high levels of government economic incentives. The simulation results are shown in Figure 6.

It can be seen that the small-scale pilot cost (CP1) for shared autonomous vehicles also has a critical value, which is between 20 and 25. From the government's perspective, when the small-scale pilot cost is relatively low (Cp1 = 15), the government's response increases the fastest and ultimately reaches a stable value of 1. As the cost increases (Cp1 = 20 and Cp1 = 25), the response growth rate slows down, and the final stable value decreases. This indicates that the small-scale pilot cost has a certain impact on the government's strategic choices, but overall, the trend is positive for the government. As the cost of small-scale pilots increases, the shared autonomous vehicle platform gradually tends towards a large-scale promotion strategy, while the growth rate and final stable strategy of shared autonomous vehicle companies are lower than those of the government. For users, they are more sensitive to the small-scale pilot cost compared to the government and shared autonomous vehicle companies, and high costs will reduce users' willingness to use the service. (3) The employment situation is severe, and the government promotes new types of employment. Based on the above analysis, this study can provide some policy and practical recommendations for the operation and development of shared autonomous vehicles. To increase user acceptance of shared autonomous vehicles, appropriate measures must be taken to enhance users' perceived safety regarding autonomous driving technology. The main current measure to alleviate the anxiety of users regarding safety risks is to equip a safety officer, which is also a requirement of current laws and regulations for the operation of autonomous vehicles. During the transitional phase toward full autonomy, the experience of using autonomous vehicles with on-board safety personnel could prove crucial for building public trust in such technology. Furthermore, people who primarily use cars for transportation place more importance on the impact of national policies, government oversight, and technical support on the development of shared autonomous vehicles than those who use public transport or non-motorized transportation. Operators and government management departments should attract users of car transportation by considering users' psychological state in their promotions, enhancing the target group's perception of the development prospects of shared autonomous vehicles, and increasing their willingness to use them. Finally, it is recommended that the government advance shared autonomous vehicles in three phases: Pilot Period (2025–2027), guiding companies' small-scale operations with economic incentives of Cg2 $\leq$ 15; Promotion Period (2028–2030), setting cost control at CP1 $\leq$ 20 while expanding service coverage; and Maturity Period (2031-future), shifting towards improving regulations and ensuring fairness.

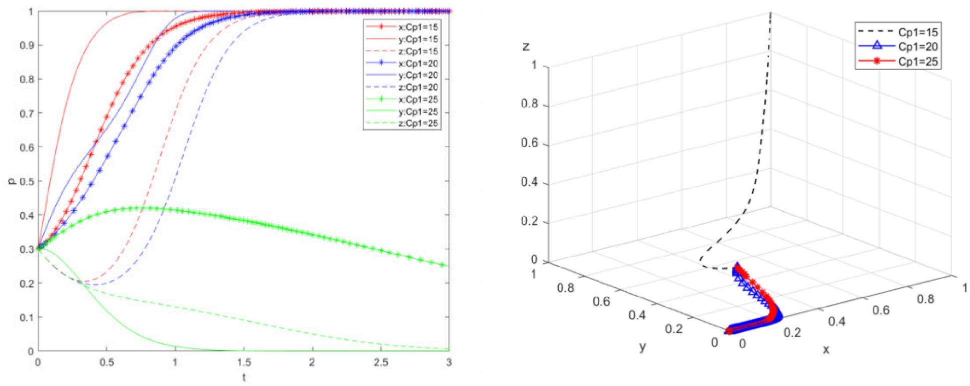

Figure 6. Evolutionary trajectories of three-party game under different economic incentive costs.

7. Conclusions

Based on the analysis of multimedia big data, this study investigates the influencing factors for travelers using shared autonomous vehicles, explores the mechanisms affecting the intention to use shared autonomous vehicles, and analyzes the multi-party games in the development process. We designed an LDA topic model to extract an extended planned behavior theory, discovering that the influencing factors encompass eight core latent variables: behavioral attitude, subjective norm, perceived risk, perceived ease of use, perceived behavioral control, behavioral intention, employment situation, and government attitude. The analysis results indicate that government attitude significantly affects users' perceived risk regarding shared autonomous vehicles: a negative government attitude exacerbates users' perceived risk, with a path coefficient of 0.497 and a t-value of 13.186; a positive attitude reduces perceived risk; and changes in employment situation (with a path coefficient of 0.434 and a t-value of 11.103) such as driver unemployment significantly enhance perceived risk. A three-party evolutionary game model gives the strategy combinations for government, platform, and potential users (economic incentives, small-scale pilot, usage) as the system's unique evolutionary stable point (E8 (1,1,1)), balancing the interests of all three parties. Based on this, the development of shared autonomy is proposed to occur in three phases: pilot phase (2025–2027), guiding small-scale operations on the platform with economic incentives of $Cg2 \leq 15$ to reduce users' perceived risk; promotion phase (2028–2030), controlling $Cp1 \leq 20$ while expanding the coverage of SAV services to enhance users' perceived ease of use; and maturity phase (2031 and beyond), focusing on the improvement of regulations (such as defining accident responsibility and protecting data privacy) and ensuring social equity (such as alleviating employment impacts).

At the empirical level of user intention, this study verifies that behavioral attitude, subjective norm and perceived behavioral control exert significant positive effects on the usage intention of shared autonomous vehicles. This finding is consistent with most existing research on the acceptance of shared autonomous vehicles based on the Theory of Planned Behavior (TPB) and Technology Acceptance Model (TAM) (PMC). Nevertheless, most domestic and foreign extant studies treat perceived risk as a direct predictor of usage intention, while few explore the antecedent effects of employment shock and government attitude on perceived risk. This study finds that government attitude ($\beta = 0.497$) and employment situation ($\beta = 0.434$) significantly affect perceived risk, which constitutes a differentiated finding rooted in the real-world context of ride-hailing and taxi driver groups in China. Several prior studies pay insufficient attention to traditional transport practitioners' unemployment concerns triggered by autonomous vehicles, and thus exclude this latent variable from their analytical models, which partially explains the divergence in their research outcomes. Meanwhile, perceived ease of use demonstrates strong positive impacts on behavioral attitude, subjective norm and perceived behavioral control in this research, aligning with the core tenets of the Technology Acceptance Model. However, the extended path from perceived ease of use to subjective norm (Hypothesis H5) has rarely been directly examined in the prior literature, and this study provides exploratory empirical evidence for this path based on short-video public opinion data and questionnaire survey data.

In terms of the simulation results of the tripartite evolutionary game, the evolutionary stable strategy derived in this study (economic incentives, small-scale pilot operation, vehicle usage) is in general agreement with the consensus of existing studies that moderate government incentives facilitate the positive evolutionary development of the industry [12]. However, some prior game-based studies tend to propose large-scale commercial rollout at the early industrial stage. By contrast, the simulation results of this research reveal that critical thresholds exist for incentive costs and pilot operation costs, rendering small-scale pilots a more appropriate strategy in the initial phase. Such discrepancy mainly stems from differences in model parameter settings: this study fully accounts for the high trial-and-error costs in the early commercialization of domestic Robotaxi services and defines small-scale pilot operation as an independent strategic alternative. Further simulation analysis indicates that the system equilibrium will shift once government economic incentive costs or platform pilot costs exceed their respective critical thresholds. This result echoes the real-world practice of Robotaxi development across multiple Chinese cities, where authorities launch small-scale pilots first before gradually expanding operational coverage.

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7.1. Theoretical Significance and Practical Implications

This study revolves around three main subjects: the government, shared autonomous driving platforms, and potential users of shared autonomous vehicles. It explores the travel choice issues of shared autonomous vehicles, providing valuable references for future travel models and enriching the theory of travel mode selection. This study applies web crawling technology, the extended theory of planned behavior, and game theory to the transportation field, examining the willingness to choose shared autonomous travel. It aims to provide theoretical support for policymakers and industry practitioners. This study helps shared autonomous vehicle companies understand their target groups, develop efficient strategies, and provide data support for user development; it also assesses user acceptance and willingness to use, guiding product design and service innovation, offering a theoretical basis for the government to formulate optimized development plans.

This article conducts an in-depth exploration of the factors influencing the willingness to use shared autonomous vehicles but does not consider the personal heterogeneity of the decision-makers. Future research could explore the impact of personal heterogeneity factors such as age, occupation, and education level on usage attitudes. The game process could incorporate stakeholders such as car operators and high-tech internet companies to more comprehensively analyze the multi-party decisions in the development of shared autonomous driving.

7.2. Research Limitations and Prospects

This paper conducts an in-depth exploration of the factors shaping residents' adoption intention toward shared autonomous vehicles. However, the data collection process has some drawbacks: the sampling covers a short time span, which means public attitudes may fluctuate over time; ride-hailing and taxi drivers account for 16.7% of the sample, a share higher than their actual proportion among the general population, which leads to the over-representation of this occupational group. Questionnaires were distributed entirely through online social networks, resulting in self-selection bias associated with social media recruitment and reducing the representativeness of the sample for the general public. Future research can adopt stratified sampling to balance the proportion of respondents from different occupations, and combine offline questionnaire collection channels to mitigate online self-selection bias, so as to further improve the external validity of research conclusions. Future research can expand the coverage and diversity of sample collection to address these limitations.

Moreover, the optimal number of topics for the LDA (Latent Dirichlet Allocation) topic model is determined merely by the combination of perplexity calculation and manual interpretability screening, without adopting quantitative semantic evaluation indicators such as topic coherence. Hence, a certain degree of subjectivity persists in topic selection. In terms of the evolutionary game analysis, all potential scenarios have not been fully discussed, and the robustness test of the model is insufficiently rigorous.

For subsequent studies, researchers can balance the sample proportion of each subgroup based on demographic attributes and occupational distribution, and supplement offline questionnaire surveys to offset the self-selection bias induced by purely online social media sampling. Multi-source social media texts from automotive forums, news comment zones and other platforms can be collected to build a cross-platform integrated corpus, so as to fully capture heterogeneous concerns of distinct user groups regarding shared autonomous mobility.

As for the validation of the topic model, researchers can systematically introduce topic coherence indicators, together with large-scale independent manual labeling by multiple coders and inter-coder reliability tests, to reduce subjective judgment during topic filtering.

Future game-theoretic research can further refine the game framework concerning public investment priority allocation and regulatory equity policy design in the mature stage of the industry [60]. Stakeholder entities such as vehicle operators and high-tech internet enterprises can be incorporated into the model to comprehensively unpack multi-agent decision-making logic throughout the industrial development of shared autonomous vehicles. In addition, future policy recommendations and implementation pathways can put forward more detailed and operable implementation policies.

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Abbreviations

The following abbreviations are used in this manuscript:

LDA	Latent Dirichlet Allocation
SAV	Shared Autonomous Vehicles

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