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Bus Drivers' Behavioral Intention to Comply with Real-Time Control Instructions: An Empirical Study from China

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Abstract: Developing intelligent bus control systems is crucial for fostering the sustainability of urban transportation. Control instructions are produced in real time by the bus control system; these are important technical commands to stabilize the order in which buses operate and improve service reliability. Understanding the behavioral intention of bus drivers to comply with these instructions will help improve the effectiveness of intelligent bus control system implementation. We have developed a psychological model that incorporates decomposed variables of the theory of planned behavior (TPB) and other influencing variables to explain the micromechanisms that determine bus drivers' behavioral intention to comply with real-time control instructions during both peak and off-peak-hour scenarios. A total of 258 responses were obtained and verified for analysis. The results showed that the influential factors in the peak- and off-peak-hour scenarios were not identical. Female drivers had greater off-peak-hour behavior intention to comply than male drivers, and there were significant differences in peak-hour behavior intention among drivers of different ages. In both peak and off-peak-hour scenarios, perceived benefit positively and perceived risk negatively affected behavioral intention. Perceived controllability positively affected behavioral intention only during peak hours. Self-efficacy only negatively affected behavioral intention during off-peak hours. Three antecedent variables (i.e., trust, mental workload, and line infrastructure support) influenced drivers' behavioral intentions indirectly via the decomposed variables of TPB. These results provide profound insights for the improvement and implementation of real-time control technology for bus services, thereby facilitating the development of smart and sustainable urban public transport systems.

Keywords: bus real-time control technology; bus drivers' behavioral intention; technology acceptance; influential factors; empirical study

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1. Introduction

The development of high frequency buses improves the urban transportation capacity and ensures the high mobility of urban residents. However, due to random variations in urban road traffic and to volatility in the distribution of passenger flow demand, bus bunching often occurs on high-frequency routes [1]; this seriously affects bus service quality and passengers' travel experiences [2,3]. Many scholars have proposed real-time control strategies for buses to solve the problem of bus bunching, including speed control [4,5], bus holding [3,6], stop skipping [7,8], and boarding limits [9,10], among others, to improve the reliability of public transport services. The real-time control strategy has been proven to perform well in simulated environments [9]. Additionally, real-time control technology developed based on these strategies has been demonstrated to perform effectively under ideal real-world operating conditions, which can improve the headway regularity in bus operation and maintain the order of the fleet [11].

Real-time control is a sustainable form of bus operation dispatching method that reduces human resource consumption, addresses bus bunching issues, and enhances the quality of bus services. Therefore, real-time control technology has wide prospects for application and contributes to the sustainability of urban transportation. Although the future of the technology is quite promising, there is still a significant gap between the theory and the practice [12]. In practical implementations, bus drivers are the executors of these real-time control instructions, and the extent to which they execute those instructions largely determines the effectiveness of control strategies [11,13,14]. As bus company employees, bus drivers' positive attitudes toward real-time control technology and their willingness to accept it are key to effectively achieving organizational goals [15]. However, existing studies have shown that bus drivers' acceptance of such technology is still low [16], which hinders its implementation and development. Examining priori acceptance before the introduction of new technology plays a key role in assisting policy makers, implementers, and technology developers in developing effective interventions to promote technology acceptance, which is crucial for the large-scale implementation of these innovations [17–21].

This study explored bus drivers' priori acceptance of technology by measuring their behavioral intention to comply with instructions. Ajzen (1991) [22] has suggested that behavioral intention predicts whether a person will engage in a certain behavior, while Davis et al. (1989) [23] defined behavioral intention as the subjective probability a person will perform a certain behavior. For respondents, questions asking about their behavioral intention are more relevant than questions asking about their general acceptance and attitudes toward a technology or system and are likely to activate more immediate concrete thinking [24,25].

This study aimed to determine the influence of bus drivers' personal attributes and social psychology factors on behavioral intention to comply with instructions in peak- and off-peak-hour scenarios in which there are differences in passenger and traffic volumes. This study contributes to the existing literature in both theory and practice. By identifying key determinants of bus drivers' compliance with instructions, it enriches the literature on bus drivers' acceptance of real-time control technology, offering insights for future technological improvement and implementation.

2. Related Work

Research on the behavioral intention of bus drivers to comply with instructions is still in its infancy. Some studies have qualitatively analyzed drivers' views and willingness to use real-time control technology via interviews and other forms [16,26]. Other studies have indirectly analyzed the response of bus drivers to real-time control instructions via testing the effectiveness of the application of such technologies in the field.

2.1. Bus Drivers' Perspectives in a Real-Time Control Context

Pritchard et al. (2014) [26] employed in-depth semi-structured interviews and ethnographic fieldwork to explore bus drivers' perspectives of location-based service (LBS) and how LBS changed their bus driving careers. They found that the introduction of LBS fundamentally changed some drivers' job roles and that drivers sought to avoid sudden speed changes to provide safe boarding and comfortable riding experiences for passengers. At the same time, this technology created some unfortunate unintended consequences for drivers, including increased workload and reduced autonomy, which led to unsafe driving. Martínez-Estupiñan et al. (2022) [16] used a questionnaire to investigate the factors that influence bus drivers to use or ignore instructions and to determine how bus drivers approach the headway control tool (HCT) to help them maintain regular headways. They found that the acceptance of real-time control technology varied by age. Experienced drivers were more reluctant to use it, as they relied more on their experience to keep regular headway, while less experienced drivers recognized the accuracy of the information delivered and felt it improved their driving performance. However, many drivers reported that road congestion, limited capacity, the deterioration of some buses, lack of adequate training, heterogeneous characteristics of other drivers, the drivers' moods, and the need to multitask while driving prevented correct execution of instructions. Almost all drivers agreed that high congestion levels and a lack of segregated lanes made it extremely difficult to comply with instructions during peak hours. The study also investigated the HCT attributes that drivers found valuable.

2.2. Bus Drivers' Behavioral Responses to Instructions

Argote-Cabanero et al. (2015) [13] conducted holding strategy simulations and inferred that the simulated results were better than the real results because the bus drivers could not fully comply with the instructions in reality, and it was hypothesized that longer holding times increased driver stress and that their compliance improved after training. Cats (2019) [27] analyzed the performance of a high-frequency line in Stockholm based on automatic vehicle location and found that drivers adjusted their driving speed based on the real-time schedule and that driver responses depended on the layout of the timepoint stops where driving performance was measured, as well as on traffic conditions. Ji et al. (2014) [28] quantified bus drivers' responses to real-time schedule adherence and their impact on transit reliability based on automatic vehicle location data; they found that bus drivers use real-time information to keep on schedule. Compared to adjusting the bus dwell times at regular stops, bus drivers are usually more likely to respond positively to real-time schedule at time point stops or to adjust their speed along the routes to keep on schedule. Lizana et al. (2014) [11] implemented real-time control software in the bus services of Transantiago; the software used the bus console or a tablet to send holding, acceleration, and deceleration instructions to drivers. They found that bus drivers did not follow the instructions they received mainly due to confusion about which instructions to follow (i.e., the instructions in the tablet or the existing schedule).

These studies initially identified key factors that influenced drivers' perceptions and responses, including perceived usefulness, perceived risk, ability to follow instructions, personal attributes, mental workload, occupational stress, driving style, and external environment. These studies provide a theoretical basis for the study of bus drivers' behavioral intentions; however, to the best of our knowledge, no research has been conducted in terms of developing a theoretical framework and quantitative analysis to explore the behavioral intention of bus drivers and influential factors oriented to real-time control technology.

Some studies have shown, however, that bus drivers' acceptance of real-time control technology varies in different scenarios. For example, during peak hours, bus drivers consider such technologies as ineffective due to road congestion and high passenger volume [16], which reduced technology acceptance. The perceptions and responses of bus drivers to such tools thus appear to be influenced by the application scenarios. However, to the best of our knowledge, no research group has studied the similarities and distinctions among the determinants of behavioral intentions during peak and off-peak hours.

Considering that the ultimately applied real-time control technology in the bus transit system is a comprehensive product formed by one or more control strategies, the main focus of this study is to explore whether bus drivers are intended to accept the real-time control instructions in general. Among diverse real-time control strategies, the holding and speed control strategies have been extensively studied and have also been proven to perform well in real-world conditions [11,29,30]. Therefore, this study takes the holding and speed control strategies as the core control strategies used, and refers to the techniques and algorithms developed by Lizana et al. (2014) [11] and Delgado et al. (2012) [9]. The technique employs a rolling horizon mathematical programming model to minimize total passenger waiting times when making each decision. The primary decision variable used to solve the optimization problem is the duration that buses should hold at a stop. If a bus should not hold, the model may suggest that the bus adjust its speed to reach its ideal position, taking into account the realistic constraints of bus speed adjustments. The optimization model is fed with static data (i.e., the number of bus stops on the line and the in-route distance between them, the average boarding and alighting times per passenger, and origin–destination demand matrix) and dynamic data (i.e., the number of buses operating in the line, their capacity and location within the bus route, speed or travel time between consecutive bus stops, passengers waiting at each bus stop and those who have boarded each bus, and speed of buses). The program estimates travel time between consecutive stops combining real-time GPS positions with historical observations. Moreover, the current technology development in China has been combined to make relevant settings for the technology, including the use of an automatic passenger counting (APC) system to collect passenger demand information, sending speed adjustment instructions to drivers each minute while driving, and sending holding instructions to drivers when buses arrive at stops. The system conveys fuzzy speed adjustment commands through panel icons indicating acceleration, deceleration, or maintaining speed, without specifying the exact speed. Drivers are allowed to adjust speed within one minute of receiving instructions (i.e., the instruction transmission frequency). Holding instructions are presented with a countdown format indicating the remaining time.

3. Theoretical Framework

3.1. Theoretical Background

The theory of planned behavior (TPB) [22] is a widely used model for predicting and describing human behaviors and has been applied to many driving-related behaviors [31–35]. The TPB posits that behavioral intentions are jointly determined by attitudes, subjective norms, and perceived behavioral control [22]. Although TPB has been universally accepted as a model for conceptualizing social behavior, it has been criticized for failing to offer operational antecedents of behavioral intention [36]. Many previous studies have further explored the feasibility of the TPB theory by considering the multi-dimensionality of its components [37–41]. As a result, the variable setting process is becoming more and more refined and close to reality.

Attitude refers to the degree to which a person has a favorable or unfavorable evaluation or appraisal of the behavior in question [22]. Based on Fishbein and Ajzen's (1977) [42] distinction of attitudes, Hsu and Chiu (2004) [38] decomposed attitudes toward a behavior into three aspects, namely perceived usefulness, perceived risk, and perceived playfulness. In this study, we focus on perceived benefit (which is similar to perceived usefulness) and perceived risk. Perceived benefits are beliefs about the positive outcomes associated with a behavior in response to a real or perceived threat [43]. Perceived risk is defined as a kind of subjective expected loss [44]. In this study, bus drivers are not only concerned about whether real-time control technology can effectively improve the level of bus service, but also pay attention to potential risks in various aspects, such as passenger satisfaction and driving safety.

Subjective norm refers to the perceived social pressure to perform or not to perform the behavior [22]. However, as real-time control technology is still in the research stage and has only been minimally implemented in certain regions, with no application in most countries (e.g., China), bus drivers may have difficulty perceiving social pressure regarding the execution of instructions. Consequently, the concept of subjective norm is not applicable in this context and is not adopted as predictors of behavioral intention in executing real-time control instructions in this study.

Perceived behavioral control (PBC) refers to people's perception of the ease or difficulty of performing the behavior of interest [22]. PBC can be decomposed into self-efficacy and perceived controllability [38]. Self-efficacy refers to confidence in one's ability to perform it [22]. Perceived controllability refers to the beliefs about the extent to which performing the behavior is up to the actor [45]. Self-efficacy and perceived controllability jointly reflect the execution difficulty from internal and external control perspectives, respectively. In the context of real-time control, some bus drivers explicitly express insufficient capability to execute instructions and a lack of control over their actions under the influence of external environmental factors, making it challenging for them to follow instructions [16].

Based on previous exploratory research, perceived benefits and risks, self-efficacy, and perceived controllability of executing instructions were four crucial antecedents for behavioral intentions in the current developmental stage in this study. Additionally, we explored antecedents of these variables, including trust, mental workload, and line infrastructure support. This framework was proposed to explain the behavioral intention to execute real-time control instructions.

3.2. Perceived Benefit, Perceived Risk, and Behavioral Intention

People construct their beliefs based on perceived benefits and risks when deciding whether to use a technology [46–50]. In the behavioral decision-making process, this is known as the risk–benefit paradigm and is seen as a fundamental predictor of behavioral willingness [49,50].

In the context of real-time control, we defined perceived benefit as bus driver' beliefs about the positive outcomes associated with the execution of real-time control instructions. Compared with private drivers and other professional drivers, bus drivers have a greater sense of social responsibility and a stronger sense of serving the public. From the drivers' perspective, the benefits associated with complying with real-time control instructions primarily refer to the social and personal benefits compliance can achieve, which can include improving headway regularity, reducing bus bunching, avoiding excessive differences in the number of passengers carried between buses, and preventing passengers from waiting too long; these help reduce angry passengers' mistreatment of the drivers [16].

Some studies have shown that bus drivers acknowledge the benefits of using real-time control technology and complying with instructions; however, they also express great concern about the associated risks [16,26]. Following Peter and Ryan's (1976) [44] suggestion, we defined perceived risk as subjective expected loss when following real-time instructions. For bus drivers, there may be dissatisfaction or anger among the passengers on the bus due to the execution of instructions such as slowing down or holding at stops [26,28]. Pritchard et al. (2014) [26] also pointed out that drivers believe that driving faster to maintain regular headway is a safety issue, which is of significant concern to bus drivers [51]. Drivers may also be concerned that complying with holding and deceleration instructions could lead to an increase in overall driving time and a decrease in driving efficiency, thereby reducing the driver's rest time. If the space at the stop is insufficient or the holding time is too long, it could also cause buses from different lines to crowd at the stop, resulting in road congestion. In this paper, perceived benefit and perceived risk are considered key factors that affect behavioral intention. We therefore propose the following hypotheses:

H1. *Perceived benefit positively affects peak-hour behavioral intention.*

H2. *Perceived benefit positively affects off-peak-hour behavioral intention.*

H3. *Perceived risk negatively affects peak-hour behavioral intention.*

H4. *Perceived risk negatively affects off-peak-hour behavioral intention.*

3.3. Self-Efficacy, Perceived Controllability, and Behavioral Intention

In the context of real-time control technology, bus drivers must be able to follow instructions and perform tasks; this involves two important factors: self-efficacy and perceived controllability. Self-efficacy [52] is associated with perceptions of control over internal factors (e.g., perceived ability or confidence to perform a behavior), while perceived controllability is associated with perceptions of control over external factors (e.g., opportunities and environmental constraints) and reflects whether the behavior depends entirely on the actor. Many empirical studies have supported this distinction [45,53,54]. Both internal control factors (e.g., the ability to adjust the bus speed according to instructions in mixed traffic or the ability to hold their buses at stops according to a given holding time) and external control factors (e.g., high traffic congestion making it difficult to adjust bus speed or limited space at bus stops making it difficult to hold the bus there) are important for complying with instructions [55].

The theory of self-efficacy proposed by Bandura (1986) [52] defined self-efficacy as "individual judgments of his capacities to complete a task," which suggests that an individual's self-efficacy affects behavioral choices and persistence. When individuals are more confident in their ability to complete a task, they are more willing to choose and stick to completing the task. Numerous studies [56–58] have shown a significant positive correlation between an individual's self-efficacy and behavioral intention and performance, as has been observed in studies related to driver behavior, such as intention to use a self-driving car [59–61] and driver speeding behavior [31,55]. The current study therefore incorporates self-efficacy into the research model, and in the context of real-time control, self-efficacy describes the confidence of bus drivers in their ability to respond to and comply with instructions [62].

Perceived controllability is defined as individual judgments about the availability of resources and opportunities to perform a behavior [45]. Individuals require certain basic conditions to complete certain behaviors [63]. Perceived controllability has been shown to predict behavioral intention in many studies; for example, Elliott (2010) [64] confirmed that perceived controllability could predict a motorcyclist's intention to accelerate and explained much of the variance, together with attitude. Kaye et al. (2020) [32] incorporated theory of planned behavior and unified theory of acceptance and use of technology constructs into regression models to predict the intentions to use highly automated vehicles, and the results showed that perceived controllability was a positive predictor of French drivers' intention to use such vehicles. In the context of real-time control, perceived controllability refers to the degree of control that bus drivers have over their compliance with instructions—that is, bus drivers' judgement about whether complying with the instructions is completely up to them because of the availability of resources and opportunities. When bus drivers have enough resources to control their behavior, they have enough confidence and are likely to be more willing to carry out instructions. Based on these findings, we propose the following hypotheses:

H5. *Self-efficacy positively affects peak-hour behavioral intention.*

H6. *Self-efficacy positively affects off-peak-hour behavioral intention.*

H7. *Perceived controllability positively affects peak-hour behavioral intention.*

H8. *Perceived controllability positively affects off-peak-hour behavioral intention.*

3.4. Trust and Perceived Benefit/Risk

Trust is a critical factor in interpersonal relationships [65]. Trust is the belief that the trustee will act cooperatively to achieve the trustor's expectations without exploiting vulnerabilities [66]. In the behavioral literature, many scholars have divided the dimensions of trust, and most scholars assess trust using the three dimensions defined by Mayer et al. (1995) [67]: ability, benevolence, and integrity. Wang and Benbasat (2004) [68] extended interpersonal trust to technological artifacts, arguing that trust in technology is essentially the same as interpersonal trust. Thatcher et al. (2010) [69] divided trust in IT into three dimensions, in which each technology trusting belief corresponds to an interpersonal trust belief, where functionality refers to the belief that a system has the capacity, functions, or features to perform a task; helpfulness refers to the belief that the system will provide adequate, responsive assistance; and predictability is the belief that a system acts consistently and that its behavior can be forecast.

Trust in technology is often used by scholars for studies on information systems [47,70,71]. Trust in technology is important for compliance with instructions because bus drivers have to evaluate whether the information provided by the real-time control technology is valid, trustworthy, and accurate, as well as providing useful guidance, to decide whether to execute those instructions. Therefore, we believe that functionality and helpfulness are the most relevant dimensions in the real-time control environment. However, it should be noted that, because most bus drivers have no experience with real-time control technology yet, trust in it more accurately refers to the initial trust of the bus driver, formed prior to first-hand experience with another party [72,73].

In the field of human–machine interaction, trust in technology provides a measurement of the subjective guarantee that technology will bring about the expected benefits or utility [74]. If bus drivers cannot trust technology, it will be difficult for them to see the benefits and usefulness of complying with the instructions sent by that technology. In multiple research fields, trust has been shown to have a significant impact on perceived benefit [50,75,76]. Therefore, it is assumed that initial trust will have a positive effect on perceived benefit in this study:

H9. *Initial trust in technology has a positive impact on perceived benefits.*

Trust can minimize the perceptions of risk and uncertainty in some cases [77,78], and perceived risk is a major factor associated with trust. Trust in technology helps reduce uncertainty when using real-time control technology and complying with instructions, thereby promoting behavioral intention. Studies from multiple research fields have demonstrated the importance of trust in explaining perceived risk and suggest that higher levels of trust weaken the level of perceived risk [79–82]. Initial trust in technology enables users to reduce their risk perceptions, increasing the likelihood that users will rely on technology to perform tasks and achieve goals:

H10. *Initial trust in technology has a negative impact on perceived risk.*

3.5. Mental Workload and Self-Efficacy

The concept of mental workload is derived from Miller's (1956) [83] theory of capacity limitation in working memory according to which people have a limited capacity and duration of working memory when processing new information. This also means that people's attention resources have a finite capacity, beyond which an increase in demand will reduce effectiveness [84]. It is therefore necessary to reduce the cognitive load of working memory and improve the ease of information processing in working memory to make it easy for people to accept new technologies [85,86]. Mental workload is defined as the cost incurred by an individual to achieve a specific level of performance on a task with specific demands [87,88].

The mental workload of drivers has been widely investigated in vehicle driving research. From the perspective of the drivers, mental workload stems from the work pressure exerted on the driver by operating the equipment or tools to complete a specific task; it has been verified to affect their work performance [89,90]. For bus drivers, attention is mostly used to ensure safe driving in the ordinary work process, and the introduction of real-time control technology is likely to cause drivers to have to pay extra attention to comply with instructions [16]. Pritchard et al. (2014) [26] also noted that drivers feel that such technologies will impose an extra work burden on them, increase their workload, and generate greater work pressure, which also exacerbates driver dissatisfaction.

Many studies have demonstrated a negative correlation between mental workload and self-efficacy [91–94]. High mental workload indicates that the formation of schemas in working memory is not smooth enough, which implies that the schema construction process associated with completing the task is complex and difficult [85,86]. Conversely, low mental workload indicates that schemas are formed in an effective and efficient manner, which leads to a more relaxed feeling when completing tasks [95]. This can also be applied to bus drivers in the context of real-time control. We believe that when drivers believe that complying with instructions requires significant extra effort, this means that it is complex and difficult for them to complete the task, so their confidence in completing those tasks will decrease. That is to say, mental workload may negatively impact self-efficacy, as confirmed by Li et al. (2021) [96] in their research on satisfaction with autonomous driving technology. Feldon et al. (2018) [97] found that the imposition of greater mental workload during instruction predicted lower levels of post-instruction self-efficacy. Therefore, our study proposes the following hypothesis:

H11. *Mental workload negatively affects self-efficacy.*

3.6. Line Infrastructure Support and Perceived Controllability

Line infrastructure is often considered an important barrier to executing real-time instructions. The current line infrastructures are still inadequate for bus drivers to carry out instructions smoothly. The holding strategy may be difficult to implement due to traffic dynamics and stop capacity constraints [28,98]. Road geometry constraints, high levels of traffic congestion and the invasion of priority bus lanes make it difficult for bus drivers to execute the acceleration and deceleration instructions [16,28].

In the field of transport-related technology acceptance and behavioral intention, previous studies have explored the impact of infrastructure support on driver acceptance, such as automated vehicle acceptance [99], electric vehicle acceptance [100,101], and transport-related cycling [102]. Therefore, we decided to include the factor of line infrastructure support (LIS) in the research model to further study its contribution to behavioral intention. LIS measures the driver's perception of how the existence of line infrastructure helps them execute instructions. Some previous studies have identified significant impacts of infrastructure availability on perceived behavioral control (PBC) [103,104]. As mentioned earlier, perceived controllability, as an underlying dimension of PBC, reflects whether the environment limits or provides opportunities to perform a given behavior, and excellent line infrastructure would enhance bus drivers' belief in their control of compliance with instructions by supporting drivers to execute instructions more smoothly. Therefore, we propose the following hypothesis:

H12. *LIS positively affects perceived controllability.*

Figure 1 shows all the factors presented in the current study and the hypothetical relationships within them. These assumptions form the theoretical framework of this study, and we tested these assumptions using structural equation models.

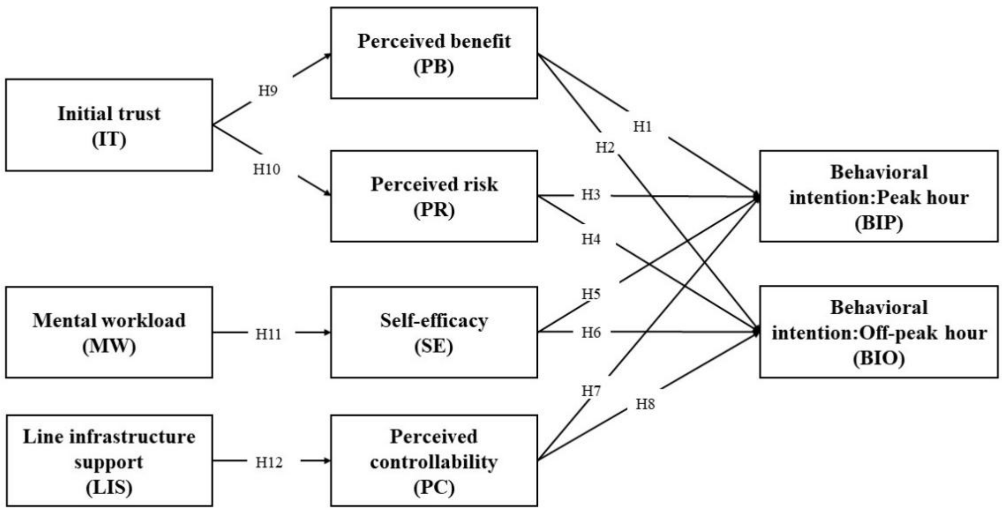


Figure 1. Research model.

4. Methodology

4.1. Questionnaire

A self-administered questionnaire was designed to collect empirical data for this study. The questionnaire consisted of three sections. The first part was used to collect five types of demographic information from the respondents: gender, age, education background, bus driving experience in years, and bus driving experience on the current route. In the second part, the respondents were introduced to the technical subjects of this study in the form of pictures combined with text, which read as follows:

While driving the bus, real-time control technology is used in the background to collect information about the real-time bus status (e.g., real-time location, number of passengers on board, number of waiting passengers at the stops, current speed, etc.) using GPS and APC devices. The travel time between consecutive stops is estimated combining the real-time information with historical observations, and real-time passenger demand data is processed. Finally, the program generates a holding instruction (staying at the stop for an additional period of time) and an acceleration or deceleration instruction every minute. The corresponding instruction is then displayed on the bus screen, requiring bus drivers to follow the instructions to avoid bus bunching.

The display screen interfaces for holding, acceleration, and deceleration instructions were also shown to the respondents. The second part focused on the measurement of the constructs proposed in our research model. There was a total of 27 items, including both self-developed and validated items adapted from previous research. These items were formed after modification based on the results of expert group discussions and interviews with eight bus drivers. Table 1 provides the final items and sources. All the variables were measured on a 5-point Likert scale, except for LIS, which was measured on a 7-point Likert scale.

Table 1. Measurement of constructs and item sources.

Constructs	Item	Sources
Perceived benefit (PB)	PB1: Complying with instructions can improve the phenomenon of bus bunching. PB2: Complying with instructions can make buses on the same route arrive at stops more regularly. PB3: Complying with instructions can prevent passengers from waiting too long for a bus. PB4: Complying with instructions can avoid excessive differences in the number of passengers carried between buses.	Self-developed
Perceived risk (PR)	PR1: Complying with instructions may lead to dissatisfaction among passengers on board. PR2: Complying with instructions may reduce driving safety. PR3: Complying with the instructions may cause traffic congestion. PR4: Complying with the instructions may reduce my work efficiency.	Self-developed, items are from [26,28]
Self-efficacy (SE)	SE1: I have enough driving ability to comply with the instructions. SE2: If I wanted to, I would be able to comply with the instructions. SE3: If I wanted to, I am confident I could comply with the instructions.	Modified from [66]
Perceived controllability (PC)	PC1: Whether I can comply with the instructions completely depends on myself. PC2: Complying with the instructions is completely under my control.	Modified from [62]
Trust (TR)	TR1: I believe that the process of generating instructions is professional, scientific, and reasonable. TR2: I believe that the technology can give accurate instructions according to actual road conditions. TR3: I believe that the technology can provide useful guidance in practical situations. TR4: I believe that the technology can provide useful guidance on my route.	Self-developed, items are from [69]

Table 1. *Cont.*

Constructs	Item	Sources
Mental workload (MW)	MW1: Mental demand MW2: Physical demand MW3: Effort MW4: Temporal demand MW5: Frustration	Modified from [87]
Line infrastructure support (LIS)	LIS1: The infrastructure on my route is generally sufficient to support me in complying with the speed control instructions successfully. LIS2: The design of the bus stops along my route (berthing resources, type of stop, etc.) is generally sufficient to support me in complying with the holding instructions successfully. LIS3: The overall infrastructure on my route is sufficient to support me in complying with real-time control instructions.	Self-developed
Behavioral intention in peak hours(BIP)	BIP: Assuming I receive instructions from the control center during peak hours, I would intend to comply with the instructions.	Modified from [16,105]
Behavioral intention in off-peak hours (BIO)	BIO: Assuming I receive instructions from the control center during off-peak hours, I would intend to comply with the instructions.	Modified from [16,105]

4.2. Procedure and Respondents

Because the studied technology is applicable to high-frequency bus routes and we wanted to conduct a behavioral intention survey for peak- and off-peak-hour scenarios, we applied the questionnaires to bus drivers on routes with departure intervals of less than 10 min during peak and off-peak hours to ensure the scientific rationale of the research. The survey was conducted both online and offline from November 2022 to January 2023, with respondents from Changsha and Fuzhou, both of which are provincial capital cities in China. Prior to participation, informed consent has been obtained from all participants. This ensured that participants fully understood the purpose and procedures of the study and voluntarily agreed to participate, while also committing to keeping their personal information confidential. A total of 281 questionnaires were ultimately collected. After removing invalid questionnaires, including incomplete questionnaires and questionnaires with obvious defects (e.g., choosing the first option for all questions or completing the questionnaire within less than 3 min), 258 valid responses remained. Most respondents were male drivers (89.1%), which is consistent with the demographics of Chinese bus drivers [106]. The basic information about the respondents (gender, age, education level, bus driving experience, and current route driving experience) is shown in Table 2.

The sample size of the study is accordant with statistical requirements. Statistical analysis of the structural equation model (SEM): the recommended sample size is 300 [107], the acceptable sample size is 200 [108]. Considering the above references, the sample size (258) is acceptable.

4.3. Analysis Methods

The model was tested using variance-based partial least-squares structural equation modeling (PLS-SEM), which is based on ordinary least-squares (OLS) regression and has several advantages that make it an appropriate multivariate analytic technique for our study [109–112]. First, it is mainly used in exploratory research and can be used for weak theory verification. Second, compared with covariance-based SEM methods, PLS-SEM is less demanding in terms of sample size requirements and does not require assumptions about multivariate normality; third, the PLS-SEM method allows latent variables to be measured by a single observed variable.

Table 2. Respondents' demographic information (N = 258).

Variable	Value	Frequency	Percentage
Gender	Male	230	89.1%
	Female	28	10.9%
Educational Background	Junior high school and below	75	29.1%
	High school diploma	95	36.8%
	Technical training	84	32.6%
	Undergraduate degree and above	4	1.6%
Age	20–29	21	8.1%
	30–39	86	33.3%
	40–49	111	43.0%
	>50	40	15.5%
Bus driving experience on the current route/years	<4	124	48.1%
	5–9	65	25.2%
	10–14	45	17.4%
	15–19	12	4.7%
	>20	12	4.7%
Bus driving experience/years	0–4	66	25.6%
	5–9	63	24.4%
	10–14	64	24.8%
	15–19	34	13.2%
	>20	31	12.0%

5. Results

5.1. Reliability and Validity Measures

Prior to estimating the structure model, we first examined the reliability and validity of the data. The internal consistency reliability, convergent validity, and discriminant validity of the measurement model were assessed. Construct reliability was tested based on Cronbach's alpha values and composite reliability (CR), which evaluates internal consistency. For each construct, a Cronbach's alpha greater than 0.8 is considered ideal and a CR value greater than 0.6 is acceptable [111]. As shown in Table 3, both the Cronbach's alpha and CR scores for all constructs were greater than 0.8, suggesting high internal consistency reliability.

To ensure convergent validity, the average variance extracted (AVE) value and standardized factor loadings were evaluated. A standardized factor loading greater than 0.7 for each factor was reliable [107]. The AVE value should be above the minimum threshold level of 0.5 [110,113]. As shown in Table 3, the factor loadings for all the items and the AVE values for all of the constructs were greater than the threshold value, confirming convergent validity.

To satisfy the requirements of discriminant validity, the square root of each construct's AVE should be greater than the value of its correlation with any other constructs [114]. The values reported in Table 4 all met these criteria, which indicates that the discriminant validity of the examined data is acceptable.

To check the multicollinearity, the values for the variance inflation factor (VIF) were measured, and the VIF values of the constructs were below 5.0, indicating that there was no obvious multicollinearity. In sum, the results showed that the reliability and validity of the measurement model were adequate.

Table 3. Reliability and validity assessments.

Construct	Item	Factor Loading	Mean(SD)	VIF	Cronbach's Alpha	CR	AVE
Perceived benefit (PB)	PB1	0.892	3.67(0.86)	3.034	0.928	0.949	0.822
	PB2	0.930	3.70(0.83)	4.308			
	PB3	0.933	3.59(0.91)	4.341			
	PB4	0.869	3.58(0.87)	2.513			
Perceived risk (PR)	PR1	0.796	3.22(0.90)	2.067	0.866	0.907	0.710
	PR2	0.733	3.06(0.93)	1.758			
	PR3	0.855	3.16(0.93)	2.772			
	PR4	0.905	3.17(0.88)	3.541			
Self-efficacy (SE)	SE1	0.911	3.66(0.82)	2.846	0.922	0.951	0.866
	SE2	0.949	3.65(0.83)	4.548			
	SE3	0.931	3.64(0.84)	3.865			
Perceived controllability (PC)	PC1	0.942	3.31(0.94)	2.866	0.893	0.949	0.903
	PC2	0.958	3.37(0.93)	2.866			
Trust (TR)	TR1	0.855	3.59(0.80)	2.362	0.930	0.950	0.827
	TR2	0.933	3.57(0.80)	4.372			
	TR3	0.938	3.66(0.77)	4.984			
	TR4	0.909	3.58(0.80)	3.703			
Mental workload (MW)	MW1	0.723	3.21(1.20)	2.603	0.904	0.915	0.684
	MW2	0.760	3.23(1.30)	3.060			
	MW3	0.807	3.22(1.30)	3.074			
	MW4	0.917	3.43(1.30)	3.283			
	MW5	0.911	3.22(1.24)	2.539			
Line infrastructure support (LIS)	LIS1	0.919	4.38(1.55)	2.990	0.887	0.930	0.817
	LIS2	0.877	4.17(1.54)	3.049			
	LIS3	0.915	4.37(1.58)	2.128			
Behavioral intention: peak hours (BIP)	BIP	1.000	3.12(1.05)	1.000	1.000	1.000	1.000
Behavioral intention: off-peak hours (BIO)	BIO	1.000	3.52(0.93)	1.000	1.000	1.000	1.000

Table 4. Correlation matrix (the Fornell–Larcker Criterion).

	PB	PR	SE	PC	TR	MW	LIS	BIP	BIO
PB	0.907								
PR	−0.091	0.843							
SE	0.580	−0.142	0.931						
PC	0.470	−0.123	0.630	0.950					
TR	0.742	−0.188	0.642	0.558	0.909				
MW	−0.227	0.332	−0.258	−0.250	−0.259	0.827			
LIS	0.612	−0.244	0.553	0.506	0.604	−0.265	0.904		
BIP	0.501	−0.260	0.463	0.456	0.515	−0.254	0.697	1.000	
BIO	0.635	−0.171	0.511	0.378	0.651	−0.105	0.598	0.590	1.000

Note: PB, perceived benefit; PR, perceived risk; SE, self-efficacy; PC, perceived controllability; TR, trust; MW, mental workload; LIS, line infrastructure support; BIP, behavioral intention, peak hour; BIO, behavioral intention, off-peak hour. The values of diagonal elements refer to the square roots of AVE.

5.2. Testing of Structural Models and Hypotheses

After establishing the reliability and validity of the data, we then examined the structural model using PLS-SEM with SmartPLS (Ver. 4.0.8.) software. The path coefficients were estimated, and then a bootstrapping algorithm was adopted to calculate the *p* values for the coefficient estimates [115]. The R^2 values were also calculated to assess the model fitting. Cohen (1988) [116] suggests that R^2 values of 0.02, 0.13, and 0.26 are the thresholds to distinguish between small, medium, and large explanatory powers for the model, respectively. We set the number of resamples to 5000 in the bootstrapping procedure. The

R^2 value for peak-hour behavioral intention and off-peak-hour behavioral intention in the model were 0.358 and 0.443, respectively, which indicates the strong explanatory power of the research model in both scenarios.

The results of PLS-SEM showed that all the hypotheses were supported except for H5 and H8, which were rejected. In addition, as high as 55.1% of variance in perceived benefit was explained by trust, suggesting that trust strongly explains perceived benefit. Meanwhile, trust accounted for 3.5% variance in perceived risk. Mental workload accounted for 6.7% variance in self-efficacy. LIS contributed to the explanation of 20% of the variance in the perceived controllability.

Comparing the salience of the path coefficients in the different scenarios revealed that the behavioral intention in different scenarios was not predicted by exactly the same factors. Factors that were significant in the peak-hour scenario were not necessarily significant in the off-peak-hour scenario, and vice versa. Table 5 provides the results of the summary analysis.

Table 5. Results of hypothesis testing.

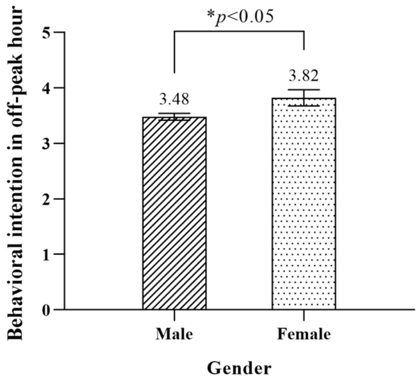
Hypothesis	Path Coefficient	*p*-Value	Supported?
H1: PB→BIP	0.316	0.000 ***	Yes
H2: PB→BIO	0.509	0.000 ***	Yes
H3: PR→BIP	−0.188	0.000 ***	Yes
H4: PR→BIO	−0.096	0.035 *	Yes
H5: SE→BIP	0.123	0.169	No
H6: SE→BIO	0.202	0.025 *	Yes
H7: PC→BIP	0.207	0.007 **	Yes
H8: PC→BIO	−0.001	0.997	No
H9: TR→PB	0.742	0.000 ***	Yes
H10: TR→PR	−0.188	0.009 ***	Yes
H11: MW→SE	−0.258	0.000 ***	Yes
H12: LIS→PC	0.506	0.000 ***	Yes

Note: PB, perceived benefit; PR, perceived risk; SE, self-efficacy; PC, perceived controllability; TR, trust; MW, mental workload; LIS, line infrastructure support; BIP, behavioral intention: peak hour; BIO, behavioral intention: off-peak hour. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

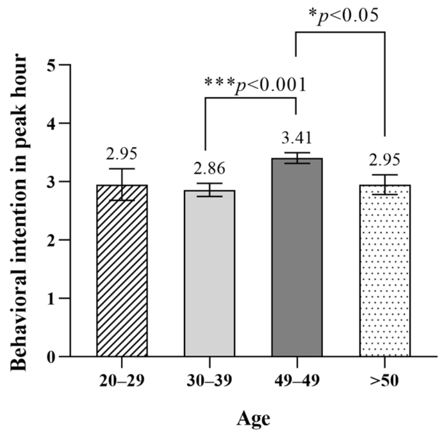
5.3. Demographic Differences in Behavioral Intention and Influencing Factors

T-tests and one-way ANOVA were adopted to test differences in demographic variables based on behavioral intention and influencing factors. Drivers of different genders ($t(256) = -2.136$, $p = 0.039$, Cohen's $d = 0.395$) and ages ($F(4, 254) = 5.238$, $p = 0.002$, $\eta^2 = 0.058$) showed significant differences in BIO and BIP, respectively. There were no significant differences in behavioral intention based on education, bus driving experience, or bus driving experience on the current route. As shown in Figure 2, female drivers ($M = 3.82$, $Sd = 0.772$) had significantly higher BIO than male drivers ($M = 3.48$, $Sd = 0.943$), and drivers aged 40–49 had higher BIP than drivers aged 30–39 ($p < 0.001$) and over 50 ($p = 0.017$).

Furthermore, it was found that the influencing factors did not differ significantly with gender, education, bus driving experience on the current route or bus driving experience. However, our results revealed that the age variable exhibited differences in three influencing factors: LIS, trust, and perceived controllability. Further multiple least significant difference (LSD) comparisons revealed that drivers aged 30–39 reported significantly lower scores of trust compared to those aged 20–29 ($p = 0.006$) and 40–49 ($p < 0.001$). The LIS scores for drivers aged 30–39 were notably lower than those aged 40–49 ($p = 0.001$). Additionally, perceived controllability among drivers aged 30–39 was significantly lower than those aged 20–29 ($p = 0.006$), over 50 ($p < 0.001$), and 40–49 ($p = 0.019$), indicating diminished scores compared to drivers in other age groups.



(**a**)



(**b**)

Figure 2. *T*-test and ANOVA results. (**a**) Differences in behavioral intention based on gender and (**b**) differences in behavioral intention based on age. * $p < 0.05$, *** $p < 0.001$.

6. Discussion

This study examined the effects of demographic variables (gender, age, bus driving years, current route driving experience, and education) and key factors (i.e., trust, perceived benefit, perceived risk, mental workload, self-efficacy, perceived controllability, and LIS) on behavioral intention in peak- and off-peak-hour scenarios. Overall, the respondents showed a moderate level of behavioral intention in both scenarios, with the average score of peak hour behavioral intention being lower than that of off-peak-hour behavioral intention. In the following sections, we discuss our theoretical findings.

6.1. Perceived Benefit, Perceived Risk, and Behavioral Intention

In both scenarios, perceived benefit positively affected behavioral intention and was the most influential factor. This finding is consistent with the fact that perceived usefulness (similar to perceived benefit) is closely related to behavioral intention [117–120]. This showed that drivers who accepted real-time control technology attached great importance to the benefits brought about by this technology in terms of decreasing passengers' travel time and improving the level of bus service. Compared with private drivers, bus drivers must consider the needs of passengers and serve the public. Bus drivers' intention to comply with the instructions was also stronger when they realized that compliance would provide better service to the passengers. Similarly, perceived risk in both scenarios negatively affected behavioral intention, which indicates that bus drivers were also concerned about the risks brought about by the technology and had certain negative views about it. In this survey, respondents worried that the introduction of the technology could cause passenger dissatisfaction, which is consistent with many previous surveys [26,28]. Bus drivers believe that holding buses not only causes dissatisfaction among passengers, but also creates pain for themselves [28]. Moreover, driving a bus slowly can also cause passenger anger, which leads to greater emotional labor for drivers [26]. Therefore, stabilizing passengers' emotions would be the priority means to reduce the risk perception to promote the implementation of real-time control technology. Meanwhile, some participants showed a lower intention to comply with real-time instructions owing to their concern about shortened rest time and decreased work performance. The execution of real-time instructions may negatively affect their work performance under the existing work performance evaluation system. Some transit companies specify daily trip frequencies and maximum trip durations for bus drivers. Following deceleration or holding instructions may extend their driving time, resulting in reduced rest intervals between successive driving shifts, and potentially reducing their work performance due to exceeding stipulated trip durations. Therefore, it is crucial for transit companies to revise their work performance evaluation systems that take into account the impact of real-time control technology on bus drivers.

Compared with perceived risk, perceived benefit was a stronger predictor of behavioral intention. Many studies [75,121–123] have shown that public attitudes toward an emerging technology are more closely related to perceived benefits than perceived risks. Therefore, when deciding whether or not to accept a technology, people are more likely to be driven by the perceived benefits than perceived risks [75], which is in line with the findings of this study.

6.2. Self-Efficacy, Perceived Controllability, and Behavioral Intention

Perceived controllability predicted behavioral intention during peak hours, but not during off-peak hours. Self-efficacy predicted behavioral intention during off-peak hours but not during peak hours. Some empirical studies have shown that self-efficacy is more influential than perceived controllability in predicting intention and behavior [55,62,124]. Interestingly, this was only supported in the off-peak-hour scenario in our study, contrary to the results in the peak-hour scenario. This indicated that, in the context of real-time control, the predictors of behavioral intention to some extent depend on the context of the execution behavior. It is therefore necessary explore the influencing factors of behavioral intention in different scenarios. One possible explanation for this result is that, compared with the off-peak-hour scenario, passenger flow and traffic volume are larger during peak hours, and road conditions are more complex and changeable; this creates a situation that imposes greater constraints on bus drivers' behavior for carrying out instructions. Although drivers have excellent driving ability, they may not be able to carry out instructions due to external environmental constraints, resulting in lower behavioral intention. The significance of external control factors in the peak-hour scenario may be greater than in the off-peak scenario, which indicates a stronger connection between perceived controllability and behavioral intention [64]. In the off-peak-hour scenario, on the contrary, the environment does not impose as many obstacles on the execution of behaviors, thus weakening the connection between perceived controllability and behavioral intention. In this case, the driver's strong driving ability becomes a motivating factor for behavioral intention. The result suggests that the main hindrance to executing instructions in peak-hour scenario is the lack of control over the behavior due to the challenging environment, while the primary obstacle to executing instructions in off-peak-hour scenario is the drivers' potential lack of ability to follow the instructions. To reduce the difficulty of executing instructions, it is crucial to customize specific instructions based on different operational periods.

6.3. Trust and Perceived Benefit/Risk

Perceived benefit and perceived risk were predicted by trust in technology, which was positively correlated with perceived benefit. It is worth noting that trust explained 55.1% of the variance in perceived benefit, which suggests that trust is a strong predictor of perceived benefit. This result is similar to those from existing studies on the adoption of emerging technologies [50,125,126], that have argued trust has a strong direct effect on perceived usefulness (similar to perceived benefit) or perceived benefit. In addition, trust in technology had a negative effect on perceived risk, which indicates that a trustworthy real-time control technology would be expected to reduce uncertainty and associated risks when complying with instructions. Based on these results, we suggest that trust in technology is a contributing factor to behavioral intention in real-time control environments. When real-time control technology is in its early stages, researchers and practitioners are more concerned about how to increase the initial trust of bus drivers in this technology.

6.4. Mental Workload and Self-Efficacy

Mental workload was found to predict self-efficacy, thereby affecting behavioral intention during off-peak hours. When drivers think that they only need to pay a small price to use the technology and comply with instructions, it means that the requirements on their driving ability are not very high, so they have greater confidence in their ability to use the technology and comply with instructions, which in turn enhances behavioral intention in the off-peak-hour scenario. When developing programs for the adoption of more efficient driving techniques, the psychological state of bus drivers must be taken into full consideration as bus drivers are among the groups of professionals that are most stressed and negatively affected by their work demands and environment [51].

6.5. LIS and Perceived Controllability

LIS was found to positively affect perceived controllability and explained a portion of the behavioral intention. This means that a high level of line infrastructure increases the degree of the driver control over the behavior of executing instructions; obtaining more resource support makes it easier to complete tasks, which leads to higher behavioral intention. Given the moderate score of LIS reported by our respondents, the inadequacy of LIS may be one of the main practical obstacles to the large-scale adoption of this technology during peak hours.

6.6. Demographic Differences in Behavioral Intention

The difference analysis of demographic variables proved that female drivers were more willing to follow instructions during off-peak hours compared to male drivers. This may be due to personality characteristics, as female drivers exhibit greater caution in their driving compared to male drivers during off-peak hours, potentially resulting in irregular-headway operation. They believe that adhering to real-time control instructions can assist them in addressing this phenomenon and provide more reliable services by keeping them informed about their position and performance along the route [16]. However, there was no significant difference in peak behavioral intention between different genders. Drivers aged 40–49 are more willing to follow instructions during peak hours compared to drivers aged 30–39 and over 50. One possible explanation is that drivers aged 40–49 have experienced continuous process of technological development empowering public transportation and perceive the new technology as a strategic and tactical decision [127], leading to stronger trust in technology. At the same time, they have a higher perception of controllability, ultimately resulting in a higher intention to follow instructions in the peak-hour scenario. The average peak behavioral intention score among drivers aged 30–39 is the lowest across all age groups, possibly due to insufficient trust in technology and lower perceived control over external factors.

7. Conclusions

7.1. Theoretical Contributions

The theoretical contribution of this study is important, and to our knowledge, it is one of the first studies to investigate the behavioral intention of bus drivers to comply with instructions in the context of real-time control.

First, this study developed a theoretical framework and demonstrated through empirical analysis that the model could largely explain why bus drivers would comply with instructions. We considered the impact of bus drivers' perceived benefit, perceived risk, self-efficacy, and the perceived controllability on their behavioral intention as well as including trust, mental workload, and LIS as antecedents to more comprehensively and deeply understand the factors affecting drivers' intention to comply with instructions. The research results indicate that the psychological processes experienced by bus drivers in their decision-making process are multidimensional. They not only attach importance to benefits and risks but also consider the difficulties of executing tasks.

Second, this study also included various driver demographic factors to discuss the impact of driver diversity on behavioral intention. We found that gender is the influencing factor of off-peak behavioral intention, and age is the influencing factor of peak behavioral intention.

Third, this study explored the importance of various factors on behavioral intention under different road traffic scenarios and further found that the focus of influencing factors on behavioral intention varied between peak- and off-peak-hour scenarios. In peak and off-peak scenarios, both perceived benefits and perceived risks can predict behavioral intention, and trust can influence behavioral intention by influencing them. In terms of the difficulties of executing instructions, drivers' perception of their controllability over the execution of instructions significantly determine their intention to follow instructions in the peak-hour scenario, while their own driving ability would be more important in the off-peak-hour scenario. At the same time, mental workload affects off-peak behavioral intention through self-efficacy, while LIS affects peak behavioral intention through controllability. The research results fill a research gap in the study of behavioral intentions of bus drivers to comply with instructions.

7.2. Practical Implications

Operating companies and developers should recognize that the development and implementation of real-time control technology cannot be separated from the acceptance of this technology by bus drivers, especially in the early application stage. A focus on the shaping of attitudes as well as the barrier of executing instructions could be of great help here. It is very important to analyze the design of headway control strategies from the drivers' perspective and develop specific implementation methods for the technology, so it is more adaptable to the mental characteristics of bus drivers, thereby improving performance. In the long run, the development of real-time control technology should first ensure that the technology can truly improve the reliability of bus service received by users in real traffic environments and minimize the risk perception of drivers. Making instructions easier to execute is also crucial.

Developers should improve the accuracy of the instructions themselves and be able to consider complex situations on the road to provide practical and useful guidance [16], such as improving the accuracy of real-time information about passenger flow and traffic conditions. In this regard, building technical capabilities within operating companies is crucial for monitoring and improving service reliability [12]. Developers should also design control strategies that consider real-world environmental factors. For example, in the practical application of bus speed optimization methods, it is important to consider the driver's ability to adjust bus speeds under constantly changing road conditions [28].

In terms of implementation, operating companies could promote and popularize the real-time control technology to bus drivers, emphasize the work and social benefits that the technology can bring, increase drivers' understanding and trust in technology, cultivate their professional pride, and enable drivers to establish the concept of serving passengers, thereby generating positive opinions. Second, companies should introduce relevant regulations to encourage drivers to use the device, such as setting a performance evaluation system that is suitable in the context of real-time control to prevent drivers experiencing job performance anxiety caused by the technology. At the same time, to avoid the risk of dissatisfaction among passengers, it is necessary to explain the existence of the technology to passengers and provide them with relevant information to improve public transportation services, such as installing an on-board screen to display the current operating status of the bus.

At the same time, ensuring the executability of following instructions is crucial, requiring careful consideration of the specific bus operation scenarios. During off-peak hours, the focus should be on enhancing drivers' internal capabilities, while in peak-hour scenarios, the emphasis should shift towards providing external resources and support. To enhance self-efficacy, operating companies should focus on and monitor the psychological states of the drivers and minimize their mental workload when using the technology. While ensuring the effectiveness of control strategies, they should try to reduce drivers' mental workload by setting an appropriate transmission frequency of instructions, among other strategies. To fully ensure driving safety, the process of reading and understanding instructions should not excessively occupy the driver's attention and should not distract the driver's attention when it is required for safe driving. Taking such human factors in the design and implementation will enable the technology to be more driver friendly. Operating companies could also provide training on real-time control technology for bus drivers to enhance their comprehension of how the system works and train them in using the device [51]. At the same time, attention also needs to be paid to driving issues [16] by, for example, guiding drivers to adjust their driving style according to the situation, thereby improving their own ability to execute instructions. To enhance drivers' perception of controllability, the government and operating companies should also establish a cooperative relationship, and traffic authorities must provide LIS for the implementation of technology when there are limited road resources, especially during peak hours with high passenger and traffic volumes. Establishing relative infrastructure for various control strategies is particularly important. For example, if a speed control strategy is adopted, the difficulties of executing instructions could be reduced by reasonable bus lane design. If a holding control strategy is adopted, bus stops should be designed to accommodate a certain number of buses. It should be noted that even with sufficient LIS, that infrastructure may not be fully functional due to the invasion of other traffic participants. Relevant regulations should therefore be formulated to ensure the availability of infrastructure.

Bus drivers must be proficient in technology and adept at addressing diverse road conditions and passenger needs to ensure passenger comfort and safety. They should maintain open communication with the dispatch center, promptly reporting any issues encountered during driving to mitigate potential risks.

Finally, when specifically implementing the technology, operating companies could adopt differentiation strategies based on the gender, age, and perceived characteristics of the bus drivers. For instance, focusing on cultivating trust in technology and enhancing perceived controllability among drivers aged 30 to 39 is deemed an effective strategy. Meanwhile, bus drivers with different attributes can be reasonably allocated based on the basic situation of bus lines and traffic conditions, thereby providing better service and maximizing benefits. For example, during off-peak hours, more female drivers can be arranged on duty. A preference for scheduling more drivers aged 40 to 49 may be considered during peak hours or other more challenging road scenarios.

8. Limitations

As one of the few studies in this field, the experience and methods of this study provide valuable insights for the study of bus driver behavioral intention in the context of real-time control, but there are limitations that should be addressed in future research.

First, as this study did not provide a real experience of real-time control technology, bus drivers lacked practical experience in its use. Their perceptions were based on prospective judgments and their imagination. Future research could provide drivers with real experience of the technology and evaluate the perceptions and behavioral intentions of bus drivers who have experienced this technology in the real world.

Second, considering that the development and application of control strategies needs to be adapted to specific conditions and that control strategies are diverse, this study did not specify or describe to drivers the range of speed adjustment and holding time during the investigation. Instead, survey respondents were provided with the technology's definition, function, and types of instructions. With the development and improvement of this technology, future work could explore bus drivers' behavioral intention based on more specific technologies or instructions.

Third, the gender distribution of the respondents in this study was uneven, as they were primarily male drivers, so survey results may lean towards the perspective of male drivers.

Finally, the samples used in this study primarily came from two cities in China. Although they meet the sample requirements for this study, the universality of the conclusions should be treated with caution. We call for cross-regional or cross-national research to strengthen the universality of the conclusions.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki. Ethical review and approval were waived for this study as it did not involve animal experiments or human clinical trials, in accordance with Chinese national policy. The study was approved by the college and conducted under its supervision.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to the protection of individuals' privacy.

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