Journal of Network Intelligence ©2022 ISSN 2414-8105 (Online)
Taiwan Ubiquitous Information Volume **7**, Number **3**, August **2022**

Integrating GOMS and UTAUT to Explain Multimodal Human-Vehicle Interaction Device User Acceptance

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Received April 19, 2022 revised June 13, 2022, accepted July 24, 2022.

Abstract. *This study integrates the GOMS model with the UTAUT model to put forward an acceptance model for multimodal human-vehicle interaction device, the GOMS-UTAUT model. The research objective is to investigate the relationship among the important controlling factors of acceptance willingness of the multimodal human-vehicle interaction device. This study investigates the users in China; a summary of 401 valid questionnaires was collected and used to test hypotheses. Data analysis includes frequency analysis, reliability analysis, confirmatory factor analysis, correlation, and structural equation modeling (SEM). According to the research purpose, this study uses Amos version 26.0 software and SPSS version 24.0 software to analyze the data, establish an SEM model and verify the hypothesis. The results are as follows: first, goals have a significant and positive impact on behavioral intention (BI), effort expectancy (EE), and performance expectancy (PE). Second, performance expectancy (PE), effort expectancy (EE), and goals significantly and positively impact behavioral intention (BI). Third, selection rules (SR), operations, methods, behavioral intention (BI), and facilitating conditions (FC) significantly and positively influences user behavior (UB) for multimodal human-vehicle interaction device. The findings have implications for other researchers to develop and study multimodal human-vehicle interaction devices.*
Keywords: GOMS, GOMS-UTAUT, UTAUT, User Acceptance, Multimodal Human-Vehicle Interaction Device (MHVID)

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1. **Introduction.** In this research, the multimodal human-vehicle interaction device consists of a speech recognition subsystem, an information interaction subsystem, a HUD subsystem, and a steering wheel control (SWC) subsystem; Figure 1 shows the device's system architecture framework. The speech recognition subsystem is used to obtain semantic information and recognize and process the semantic information; the SWC subsystem sends commands through physical methods and completes corresponding operation items; the information interaction subsystem receives instruction information and performs relevant operations. The HUD subsystem displays the interactive data. The speech recognition and the SWC subsystems connect to the information interaction subsystem, and the information interaction subsystem connects to the HUD subsystem.

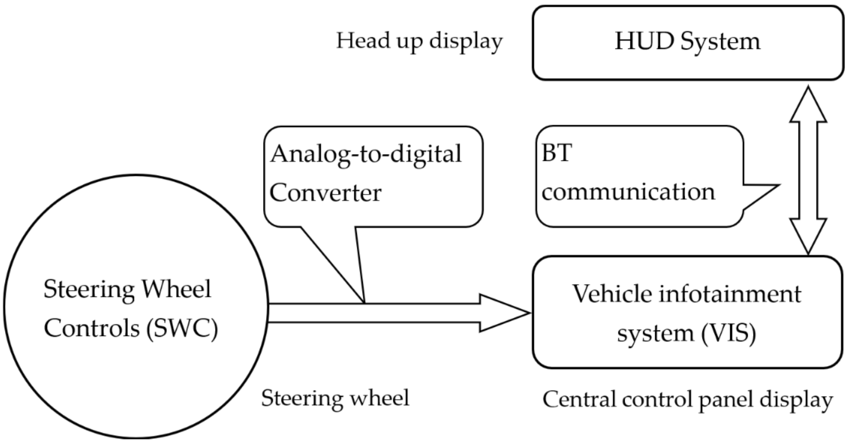

FIGURE 1. System architecture framework

Figure 2 is the multimodal human-vehicle interaction device's working schematic. The SWC subsystem includes four direction buttons and a confirmation button, which control the information interaction subsystem. The HUD is mainly used to display the contents of the center console display, which is an extension of the center console display. In this way, the driver does not need to touch the display screen during driving but only needs to operate through the speech or physical buttons on the steering wheel, and the operation results are displayed on the HUD screen and the center console's display screen so that the driver can watch through the HUD. The driver does not need to look at the center console display for the operation result and avoid driving distractions.

A survey report by Newsijie, a leading consulting company focusing on China's automotive industry, shows that in 2019, the global penetration rate of multimodal human-vehicle interaction equipment was about 9.3%, of which the penetration rate of Chinese multimodal human-vehicle interaction equipment was less than 2.6%, far lower than the global average [1]. The multimodal equipment mentioned in this study adopts a new interaction method. The researchers must understand the factors that affect users' adoption and use of this multimodal human vehicle interaction equipment. Researchers and manufacturers will be able to address the bottlenecks that hinder users' adoption and improve their services.

The study integrates UTAUT with GOMS models to research the acceptance factors of the multimodal human-vehicle interaction device. The findings show that these two factors significantly affect user behavior. The study made three contributions. Firstly, the existing user acceptance research of HCI equipment focuses on the users' technology perception or uses GOMS to evaluate the interface through the users' cognitive process. At present, no researchers integrate the two models to research the multimodal human-vehicle

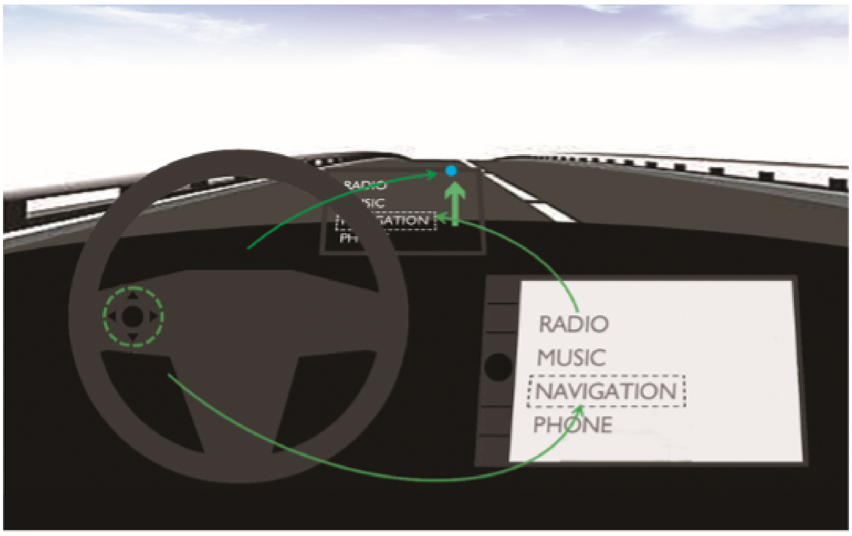

FIGURE 2. Working diagram of multimodal human-vehicle interaction device

interaction device; this research integrates UTAUT and GOMS to explain user adoption behaviors and explore this gap. Secondly, the study shows that goals will affect effort expectancy, performance expectancy, and behavioral intention; selection rules, operations, and methods influence user behavior; these show the importance of GOMS. Third, the GOMS-UTAUT model explains more user adoption variance than the GOMS and UTAUT models alone, indicating the integrated model's explanatory advantage.

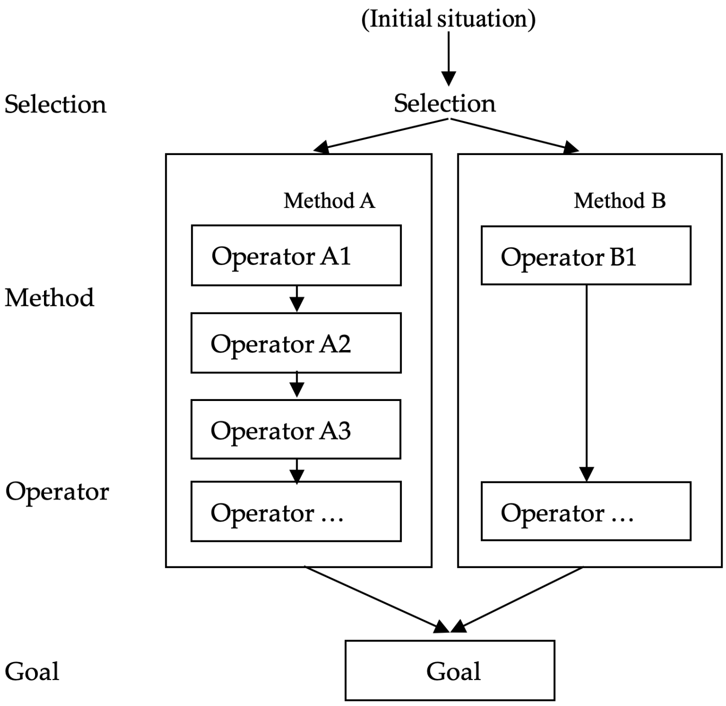

FIGURE 3. The GOMS model [2]

2. Literature Review, Research Hypothesizes, and Research Model.

2.1. **Literature Review.** According to Rhiu et al., [3] most of the research are mainly related to safety and adaptability features (for example, driver's status recognition, vehicle surrounding monitoring, and driver's action suggestions), while the research on human-computer interaction of infotainment (for example, information technology, vehicle interaction) is relatively insufficient. The core problems of human-computer interaction of intelligent connected vehicles that need to be further solved include technology acceptance, human-computer interaction quality, and user experience [4]. Among the human factors, user acceptance and trust significantly impact the sustainable development of autonomous driving and user satisfaction. Higher customer satisfaction can bring business advantages to future vehicle suppliers [5].

Card et al. [2] first proposed the GOMS model in "HCI psychology," presented in Figure 3. The GOMS model describes the user's behavior through Goals, Operations, Methods, and Selection rules [2]. During the procedure of human computer interaction, the GOMS model can regard the establishment of a user model as the process of solving problems. Firstly, the tasks are analyzed using the GOMS model, and the user's intention is determined and classified. Specify the user's operation to accomplish the goal and choose the best method based on the user's intention. If multiple methods exist to achieve a goal, the user must obey the selection rules to select the best method. GOMS is considered one of the few mature and well-known theoretical models of the HCI interface [6]. It is a significant theory guiding designers to design an HCI system [7] and evaluate the quality of the HCI interface. GOMS is intended as a system design methodology that is used for modeling different tasks in various areas, for example, extensive computer tasks [8, 9], testing user interface designs [9, 10, 11], and user interface analysis [9, 12].

Researchers are actively applying the GOMS theory to HCI systems. Karwowski et al. of the University of Louisville [13], when exploring the effectiveness of the fuzzy approach in HCI analysis and design, summarized the framework of the GOMS model and proposed the GOMS model, the fuzzy version, and the experimental verification process. Christou et al. [14] extended the GOMS model to form a new codeine model for evaluating reality-based interaction interfaces. Oyewole and Haight [15] proposed an expert system based on the GOMS model to provide the necessary guidance to help users achieve their mission goals while browsing the web. Amant et al. [16] used the GOMS model to accurately predict and evaluate the user's interaction behavior when using mobile phone menus. Li [17] analyzed the advantages and disadvantages of GOMS. Its derivative behavior model proposed a suitable human-computer BHR-GOMS behavior model for the interaction interface design and was used to assess the performance of various operating modes in the door opening and closing behavior. Chen and Shi [18] used the GOMS model to analyze cognitive tasks of scientific discovery learning and decompose it into understanding problems, exploring local models, and synthesizing global model and reflection to evaluate four sub-goals.

Venkatesh et al. [19] conducted a longitudinal study and compared UTAUT with eight other models: TRA, TPB, TAM, C-TAM-TPB, MM, MPCU, IDT, and SCT. The research found that the prediction power of the other eight models for the behavioral intention was between 17% and 53%. At the same time, that of UTAUT reached 70%, which was better than any other theoretical model. UTAUT is a helpful tool to evaluate technology user behavior. Since 2007, researchers have been increasing their research on the UTAUT model, which has various applications in information systems, e-commerce, wireless LAN technology, mobile technology, and other fields. Research on the combination and extension of the UTAUT model and other factors is also developing. Xu [20] used the TOE framework and UTAUT model to study the acceptance of the organizational information systems, integrated organizational and individual adoptions into a model framework for research, and initially explored the impact factors of organization adoption in the dynamic technology environment to promote personal adoption. Jung and Fu [21] combined UTAUT and TTF to study the acceptance of the CRM system. Although the UTAUT model has wide adaptability and reliable explanatory power, there are still some shortcomings, such as the lack of model consideration of the possibility of secondary acceptance of technology and neglecting the individual satisfaction study [22, 23]. The four core influencing factors in the model can explain and predict an individual's acceptance of information technology well, but their respective forces will differ in different fields [19].

Davis [24], Taylor & Todd [25], and other researchers pointed out that in the research of acceptancy behavior of specific technology, researchers can readjust the relationship between models and variables according to the situation and can exact factors with high correlation from different theoretical frameworks for their research. This study integrated the GOMS model with the UTAUT model to propose a GOMS-UTAUT model to evaluate multimodal human-vehicle interaction device user behavior. It adjusts some research variables to make it more suitable for multimodal HCI equipment.

2.2. **Multimodal human-vehicle interaction device UX Analysis Based Research Hypotheses.** Performance expectancy is similar to TAM's perceived usefulness and IDT's comparative advantage [19]. It demonstrates the user's perception of the multimodal human-vehicle interaction device's safety, efficiency, rapid response, effectiveness, accuracy, and other performance improvements. Effort expectancy approaches the TAM's perceived usefulness and IDT's complexity [19]. It shows the user's opinion on how difficult it is to operate the multimodal human-vehicle interaction device. Based on the UTAUT model, effort expectancy positively impacts performance expectancy [19]. When drivers find the multimodal human-vehicle interaction device is helpful and easy to use, they will have a high expectancy for its performance; Otherwise, their performance expectancy will be poor. Facilitation conditions are the same as TPB's perceived behavioral control, reflecting the influence of user knowledge, abilities, and resources [19]. As a new type of HCI equipment, users need specific knowledge and operation skills, such as connecting a mobile phone to make calls. If users lack these operating skills, they will not adopt or use the multimodal human-vehicle interaction device. Many researchers found that perceived cost significantly influences the acceptance and use of IT devices [26, 27, 28, 29, 30]. Previous studies have revealed the impacts of performance expectancy, effort expectancy, and facilitating conditions on users' behavioral intention. Therefore, we hypothesize:

H1: The facilitating conditions of the multimodal human-vehicle interaction device positively impact user behavior.

H2: The user's performance expectancy for the multimodal human-vehicle interaction device positively impacts behavioral intention.

H3: The user's behavioral intention for the multimodal human-vehicle interaction device positively influences user behavior.

H4: The user's effort expectancy for the multimodal human-vehicle interaction device positively influences behavioral intention.

"Goals" is used to describe the action intention that the user wants to achieve. It can break an action down into many more minor steps. For example, the purpose of an action is to make a call, which can be divided into entering the main menu, clicking to enter the call interface, entering the dialing command, inputting the phone number, dialing, and other sub-objective. Therefore, using the multimodal human-vehicle interaction device, whether achieving the goal safely, efficiently, and accurately directly impacts the driver's behavioral intention, performance expectancy, and effort expectancy. Thus, we hypothesize:

H5: Goals positively affect the user's performance expectancy to the multimodal human-vehicle interaction device.

H6: Goals positively affect the user's effort expectancy for the multimodal human-vehicle interaction device.

H7: Goals positively influence the behavioral intention to use the multimodal human-vehicle interaction device.

"Selection rules," when there are multiple methods to reach the goal, describe how to choose the application method according to the current situation. When trying to achieve a goal, users usually have multiple ways to reach it. This research believes that the optimal selection rules will positively affect the user behavior of the multimodal human-vehicle interaction device. So, we have:

H8: The multimodal human-vehicle interaction device's selection rules positively impact user behavior.

"Operations" refer to each action of the multimodal human-vehicle interaction device used to complete a task, such as aiming at the icon, clicking the screen, and adjusting the volume. The operations are the user's perception, cognition, or neural action necessary for using an interactive system. Therefore, they may affect the system's state or the user's psychological condition, affecting the drivers' user behavior of the multimodal human-vehicle interaction device. Therefore, in this research, we hypothesize:

H9: The operations for the multimodal human-vehicle interaction device positively influence the adoption and use of behavior.

"Methods" describe a series of operations' processes to achieve the goals. This research used methods to explain the operation process of the driver completing the multimodal human-vehicle interaction device to execute the goals. There can be different methods for the same purpose. So, in this research, we hypothesize:

H10: The methods of using the multimodal human-vehicle interaction device positively impact the adoption and use behavior.

Voluntariness, there is no compulsion to use a multimodal human-vehicle interaction device, and the device's application is primarily voluntary. The driver can freely choose whether to use it, and there is no pressure from laws and regulations or driving requirements. Therefore, the effect of voluntariness is little. In the research model construction of this paper, voluntariness is not explicitly considered regulation.

"Social influence" means "the extent to which individuals feel the influence of surrounding groups." The specific social impact in this study refers to the influence of colleagues, classmates, and relatives. The device is installed in the dashboard, and the cockpit is a relatively closed space with individual privacy. The drivers who use the device mainly consider safety, availability, and ease of use; the social influence is relatively small. Therefore, there is no specific consideration of the regulatory role of social impact in the model construction.

According to the summary of scholars' research results and the above analysis, combined with the characteristics of the multimodal human-vehicle interaction device, this article proposed the conceptual model to study the composition of variables and corresponding research hypotheses, as shown in Figure 4. The conceptual model retains some of the research variables of the original UTAUT model, including facilitating conditions, performance expectancy, effort expectancy, behavioral intentions, and user behavior, integrating the GOMS model's goals, selection rules, operations, and methods.

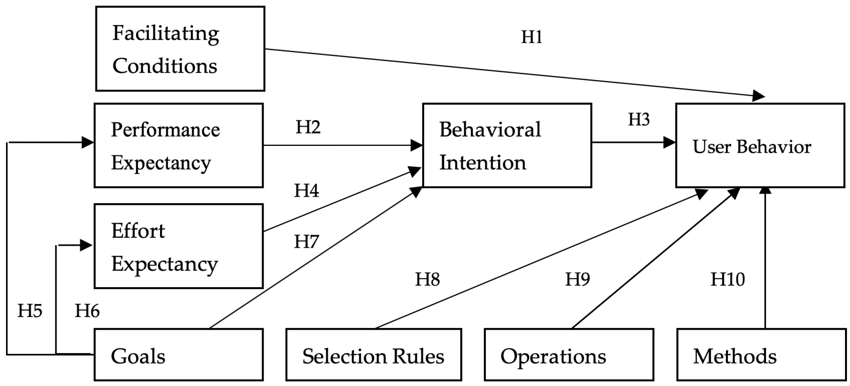

FIGURE 4. The research hypotheses and GOMS-UTAUT conceptual model

3. Methods for User Experience Analysis Based on Multimodal Human-vehicle interaction devices.

3.1. **Samples.** In June 2021, there were 380 million drivers in China. Following the recommendations of Boyd et al. [31], Comrey et al. [32] and Hair et al. [33] and the research hypotheses, the minimum sample size was 384.

This research experimented in Huizhou Foryou General Electronics Co., Ltd., a Chinese leading automotive electronics company. This study selected a convenient sampling method from non-probability sampling methods. Participants were publicly recruited within the company and selected those with driving experience from the applicants.

Four hundred fifty-seven employees participated in the experiments, distributed 457 questionnaires, and 436 returned. Thirty-five responses were discarded owing to unanswered or biased answers. The remaining 401 valid questionnaires were further analyzed, as shown in Table 1. Therefore, the final response rate was 87.7%.

TABLE 1. Characteristics of multimodal human-vehicle interaction device Users

Variable	Level	Frequency	Percent
Gender	Female	100	24.9
	Male	301	75.1
Age	18-24	41	10.2
	25-39	256	63.8
	40-54	103	25.7
	> 54	1	.2
Driving experiences	0-3	170	42.4
	3-5	99	24.7
	5-8	70	17.5
	> 8	62	15.5
IVIS experiences	0-3	155	38.7
	3-5	106	26.4
	5-8	82	20.4
	> 8	58	14.5
	Total	401	100.0

3.2. **Research Instrument.** There are three parts to the questionnaire (see Table 2). Part I asks participants to provide demographic data, including age, gender, and driving experience. Part II is about the UTAUT. Part III is about the GOMS. The questions of the UTAUT part are derived from Venkatesh, Morris, Davis, and Davis' original list of items used in estimating UTAUT [34] and are slightly modified as typically done in previous UTAUT studies such as [35, 36], only to match the subject material of the study appropriately. The researcher drafted the GOMS items in the questionnaire first; After discussing with many professors and well-known experts in the HCI area, the questionnaire was sent to 15 experts and senior drivers by e-mail for their opinions. Finally, this research form questions according to their views. Part II and part III consist of Likert five-point scale interval-level response statements.

Table 2. Summary of questionnaire items

Scale	Item	Number of questions
UTAUT	performance expectancy (4) effort expectancy (4) facilitating conditions (4) behavioral intention (3) use behavior (3)	18
GOMS	Goals (4) Operations (4) Methods (4) selection rules (4)	16
Demographic	Gender, Age, Driving experiences, IVIS experiences	5
Total		39

3.3. **Data Collect Procedure and Data Analysis Tools.** The study used the GOMS-UTAUT scale to collect the data on the user experience of the multimodal human-vehicle interaction device, and the procedure is as follows:

The experiment projected the driving scenarios on the front LCD, which was set in front of the driver. Before the investigation, the subjects were asked to maintain a comfortable driving posture in front of the static driving simulator and practice for about 10 minutes to get familiar with the driving simulator and the multimodal human-vehicle interaction device. The experiment required the subjects to complete a series of HCI tasks while driving and fill in the questionnaire before task reporting or discussion.

According to the research purpose, this study used SPSS version 24.0 software and Amos version 26.0 software for data analysis and hypotheses test.

3.4. **Reliability and Validity Tests.** Even many professors and well-known experts in the HCI area verified the questionnaire contents; this research also used Cronbach's α coefficient to test the reliability. Table 3 demonstrates the statistically analyzed results of the Cronbach reliability test. The average value of α on all scales is above 0.7, and the overall Cronbach's α coefficient is 0.939, indicating good reliability.

3.5. **Convergent Validity Test.** Table 4 shows the convergent validity test result; All constructs' factor loadings are between 0.609 and 0.799, which are significant; The composite reliability (CR) is between 0.693 and 0.826; The square of the multivariate correlation coefficient (SMC) ranges from 0.504 to 0.563, which are in line with the criteria of Hair et al. [33] and Fornell et al. [37]: loading factor > 0.5; CR > 0.6; Average Variance Extracted (AVE) > 0.5. SMC > 0.5. BI3, FC1, and UB2's SMC parameters are slightly lower than

Table 3. Reliability test

Factor	Items	N of Items	Cronbach's Alpha	Overall reliability
UTAUT	FC	4	0.742	0.939
	PE	4	0.803	
	EE	4	0.828	
	BI	3	0.760	
	UB	3	0.765	
GOMS	Goals	4	0.851	
	SR	4	0.774	
	Operations	4	0.839	
	Methods	4	0.834	

0.5, but it is still acceptable, and the rest meet the criteria, so the nine constructs have convergent validity.

Table 4. Confirmatory factor analysis results

Factor	Indicator	Unstandardized Factor Loadings	SE.	CR.T-Value	P	Standardized Factor Loadings	SMC	CR	AVE
BI	BI1	1.000				.709	.503	.763	.520
	BI2	1.199	.116	10.354	***	.801	.642		
	BI3	.925	.089	10.344	***	.645	.416		
EE	EE1	1.000				.681	.464	.829	.549
	EE2	1.291	.100	12.896	***	.797	.635		
	EE3	1.171	.093	12.654	***	.770	.593		
	EE4	1.138	.095	11.932	***	.710	.504		
FC	FC1	1.000				.699	.489	.766	.522
	FC2	.938	.088	10.628	***	.727	.529		
	FC3	.987	.093	10.624	***	.740	.548		
Goals	Goal1	1.000				.722	.521	.852	.590
	Goal2	1.081	.077	14.124	***	.783	.613		
	Goal3	1.197	.082	14.655	***	.826	.682		
	Goal4	1.068	.080	13.409	***	.738	.545		
Methods	Method1	1.000				.717	.514	.822	.537
	Method2	1.046	.083	12.606	***	.737	.543		
	Method3	.962	.074	12.950	***	.768	.590		
	Method4	.884	.072	12.202	***	.707	.500		
Operations	OP1	1.000				.738	.545	.840	.569
	OP2	1.109	.075	14.697	***	.833	.694		
	OP3	.903	.069	13.087	***	.713	.508		
	OP4	.972	.073	13.323	***	.727	.529		
PE	PE1	1.000				.731	.534	.802	.574
	PE2	1.136	.092	12.369	***	.793	.629		
	PE3	1.033	.084	12.309	***	.748	.560		
SR	SR1	1.000				.725	.526	.781	.543
	SR2	1.095	.097	11.333	***	.771	.594		
	SR3	1.002	.089	11.282	***	.713	.508		
UB	UB1	1.000				.741	.549	.767	.523
	UB2	.997	.094	10.659	***	.701	.491		
	UB3	.951	.089	10.698	***	.727	.529		

3.6. **Discriminant Validity Analysis.** Table 5 shows the correlation and discriminant validity of the latent variables based on Fornel & Lacker [38] and Hair al et. [33]. Each construct's AVE is greater than the squared correlation between constructs. So, the discriminant validity of all constructs is sufficient.

Table 5. Discriminant validity

Factor	AVE	Goals	Methods	Operations	BI	UB	EE	SR	FC	PE
Goals	.590	.768								
Methods	.537	.553	.733							
Operations	.569	.727	.489	.754						
BI	.520	.805	.549	.704	.721					
UB	.523	.412	.485	.568	.665	.723				
EE	.549	.774	.543	.756	.826	.482	.741			
SR	.543	.590	.448	.547	.651	.517	.558	.737		
FC	.522	.359	.314	.326	.413	.380	.450	.275	.722	
PE	.574	.747	.458	.610	.776	.379	.748	.477	.304	.758

4. Results.

4.1. Multicollinearity Analysis. Zahari et al. [39] explain, "multicollinearity presents when the independent variables variance inflation factor (VIF) values > 10 among themselves." Model results are poor and misleading when used the variables as predictors, and their interdependence is strong enough. Table 6 shows the "VIF" values; all are less than 10, meaning no multicollinearity.

TABLE 6. Multi-collinearity Analysis

Construct	User-behavior		Behavioral Intention		Effort Expectancy		Performance Expectancy	
	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF
FC	.885	1.130						
Goals	.526	1.900						
Operations	.577	1.732						
SR	.703	1.422						
Methods	.736	1.358						
PE			.497	2.013				
EE			.499	2.005				
Goals			.472	2.120	1.000	1.000	1.000	1.000

4.2. Overall Model Fitness Test. Figure 5 shows the standardized coefficients of the model.

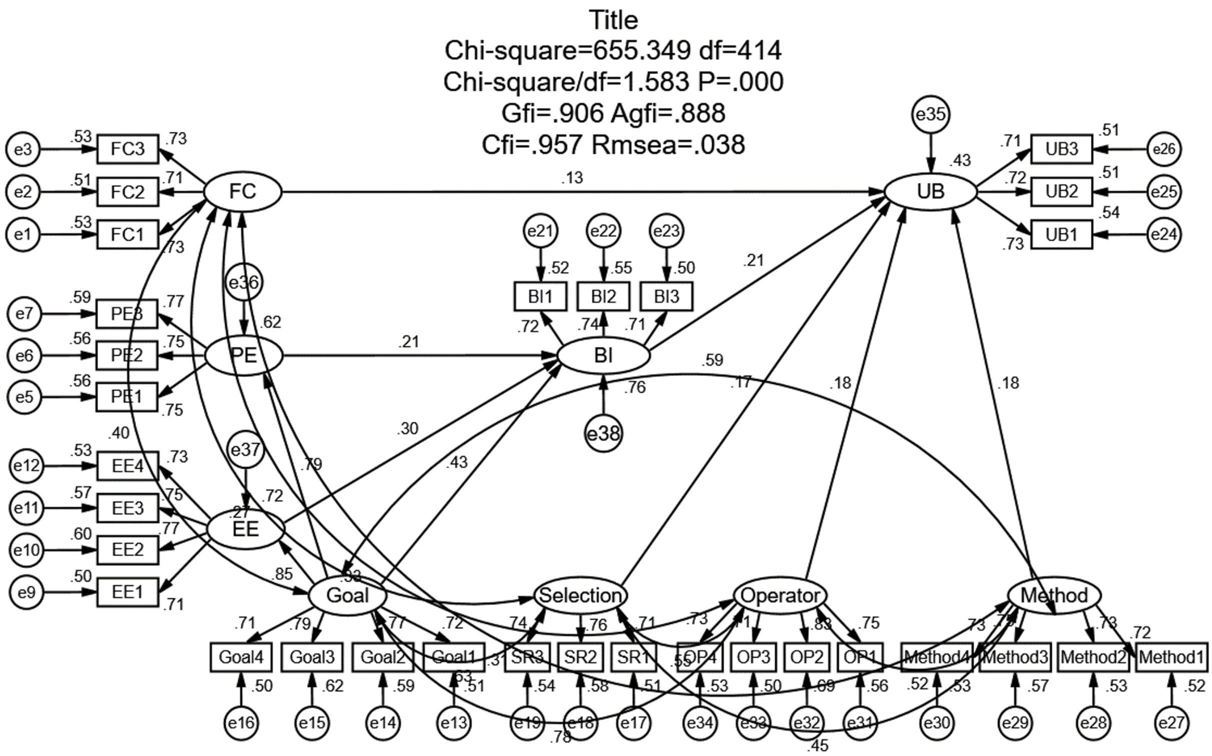

FIGURE 5. Overall results of the UTAUT-GOMS SEM model

According to the opinions of Hoyle and Panter [40] and McDonald et al. [41], this study selected several indexes to evaluate the overall model fitness, including Chi-square degrees of freedom, GFI, AGFI, RMSEA, NNFI, IFI, CFI, and SRMR.

Table 7 presents the overall model fitness. The AGFI value equal to 0.888 is slightly lower than 0.9 but in the range of 0.80 to 0.89, which is reasonable [42, 43], and other values meet the ideal standard indicators. So, all fitness indicators align with the general SEM research criteria.

Table 7. Overall model fitness

Fitness Index	Ideal Standard Indicators	MHCI-ICAR Model Fitness Index
χ^2	the smaller, the better	655.38 (p = .000)
χ^2/df	< 3	1.583 (DF = 414)
GFI	> .9	.906
AGFI	> .9	.888
RMSEA	< .08	.038
SRMR	< .5	.046
TLI (NNFI) ho2	> .9	.952
IFI Delta2	> .9	.958
CFI	> .9	.957

According to the effect size defined by Chin [44] and Henseler et al. [45], the effects can be classified as low effect (R^2 between 0.19 and 0.33), moderated effect (R^2 between 0.33 and 0.67), and large effect (R^2 value greater than 0.67), the higher level, the higher predictive accuracy. Table 8 shows that the transformation probability for the selected model was between medium and large, indicating an excellent fit to the selected independent variables.

Table 8. The SMC test result

Dependent Variable	SMC
EE	.723
PE	.621
BI	.764
UB	.431

Table 9 shows that facilitating conditions, selection rules, operations, methods, and behavioral intention impact user behavior significantly. The goals, effort expectancy, and performance expectancy significantly affect behavioral intention, and goals significantly affect performance expectancy and effort expectancy.

Table 9. Path regression weight and significance test results

	Path	Unstandardized Estimate	Standardized Estimate	SE.	CR. T-value	P Value	Result
H1	Facilitating Conditions → Use Behavior	.098	.134	.046	2.134	.033	Accepted
H2	Selection Rules → Use Behavior	.162	.168	.073	2.202	.028	Accepted
H3	Operations → Use Behavior	.135	.179	.066	2.048	.041	Accepted
H4	Methods → Use Behavior	.139	.177	.056	2.493	.013	Accepted
H5	Behavioral Intention → Use Behavior	.177	.208	.083	2.138	.033	Accepted
H6	Goals → Behavioral intention	.450	.426	.138	3.253	.001	Accepted
H7	Effort expectancy → Behavioral Intention	.310	.303	.111	2.782	.005	Accepted
H8	Performance expectancy → Behavioral Intention	.209	.210	.087	2.394	.017	Accepted
H9	Goals → Performance Expectancy	.837	.788	.072	11.622	***	Accepted
H10	Goals → Effort Expectancy	.880	.850	.075	11.768	***	Accepted

5. Discussion.

5.1. **Analysis of the Relationship Between UTAUT and Multimodal Human-Vehicle Interaction Device User Behavior.** The model in this research hypothesized that the facilitating conditions of the multimodal human-vehicle interaction device would positively impact user behavior (H1). The research findings show that facilitating conditions significantly and positively affect user behavior, which means that facilitating conditions are important in determining the acceptance of the multimodal human-vehicle interaction device. The result is consistent with M. T. Dishaw and Strong [46] and Zhou et al. [30]. Therefore, this study provides empirical evidence that is facilitating conditions influence users' beliefs on the acceptancy of the multimodal human-vehicle interaction device.

This research hypothesized that the users' performance expectancy for the multimodal human-vehicle interaction device positively impacts behavioral intention (H2). The parameter estimates results for the hypothesis were positive and statistically significant; this suggests that performance expectancy positively affects behavioral intention for the user behavior of the multimodal human-vehicle interaction device. Thus, the hypothesis is accepted. Several studies [24, 47, 48, 49] have demonstrated the significant impact of performance expectancy on adopting information systems. This finding shows that users' positive perceptions of performance expectancy drive the adoption of multimodal human-vehicle interaction devices. In conclusion, the findings of this hypothesis are the same as previous studies, indicating that performance expectancy plays an important role in determining and shaping the behavioral intention of adoption and use of the multimodal human-vehicle interaction device.

This study hypothesizes that the user's behavioral intention for the multimodal human-vehicle interaction device positively influences user behavior (H3). The parameter estimates results for the hypothesis were positive and statistically significant; this suggests that behavioral intention for the multimodal human-vehicle interaction device positively influences user behavior. Thus, the hypothesis is accepted. This research suggested that behavioral intention impacts user behavior significantly. The result is the same as the previous studies [24, 50]. The present research findings suggest that behavioral intention was an essential determinant of user behavior, significantly influencing users' toward adopting and using the multimodal human-vehicle interaction device.

The model in this study hypothesizes that effort expectancy for multimodal human-vehicle devices positively impacts their behavioral intention of acceptance and use (H4). The parameter estimates results for the hypothesis were positive and statistically significant; therefore, the hypothesis was accepted, which postulates that effort expectancy is the factor that influences behavioral intention to accept the multimodal human-vehicle interaction device. Previous studies [19, 51] have proved a positive correlation between effort expectancy and behavioral intention toward adopting and using new information systems. Thus, this study provides empirical evidence to support the proposition that effort expectancy influences user behavior intentions. The research model proposes that effort expectancy for the multimodal human-vehicle interaction device positively affects behavioral intention.

5.2. **Analysis of the Relationship Between GOMS and Multimodal human-vehicle interaction device Use Behavior.** The goals are from the GOMS model. This study hypothesizes that goals positively impact users' performance expectancy for the multimodal human-vehicle interaction device (H5). The parameter estimates for this hypothesis are positive and statically significant, so the hypothesis was accepted. This study confirms that the goals impact user performance expectancy for multimodal human-vehicle interaction device and indirectly affects users' behavioral intention.

This study hypothesizes that goals positively affect users' effort expectancy for the multimodal human-vehicle interaction device (H6). The parameter estimates for this hypothesis are positive and statically significant, so the hypothesis was accepted, implying that goals positively influence effort expectancy and play an essential role in determining and shaping users' effort expectancy for the multimodal human-vehicle interaction device.

This research hypothesized that goals would significantly influence drivers' behavioral intention toward the multimodal human-vehicle interaction device (H7). The parameter estimation results of the hypothesis show that the correlation of the hypothesis is statistically significant, so the hypothesis was accepted. The finding suggested that goals significantly affect behavioral intention, implying that goal is essential in the behavioral intention perceptions of adopting the multimodal human-vehicle interaction device.

The model in this study hypothesizes that the selection rules would significantly impact the driver's user behavior of the multimodal human-vehicle device (H8). This hypothesis was derived from the GOMS model, and the parameter estimation results were statistically significant. Therefore, this hypothesis is accepted. The results show a positive correlation between the selection rules and the user behavior. This study provides empirical evidence that selection rules significantly impact the user behavior of the multimodal human-vehicle device. Therefore, Selection Rules are an important and positive predictor of the multimodal human-vehicle interaction device's user behavior.

This study hypothesized that operations would significantly impact multimodal HCI equipment's user behavior (H9). The parameter estimation results show that the hypothesis is statistically significant, so the hypothesis is accepted. The results suggest that the operations positively influence user behavior, which indicates that the operations are a significant factor in determining the adoption behavior of the multimodal human-vehicle interaction device. Therefore, this research has provided empirical evidence to support that operations affect drivers' beliefs about the multimodal human-vehicle interaction device.

The methods were drawn from the GOMS model. This research hypothesized that methods would significantly influence the user behavior of the multimodal human-vehicle interaction device (H10). The parameter estimates showed that the hypothesis was statistically significant; therefore, the hypothesis was accepted. The findings suggest that the methods significantly affect user behavior, implying that methods are important in determining the adoption and user behavior of the multimodal human-vehicle interaction device.

5.3. **Discussion of the Multimodal human-vehicle interaction device Acceptance.** The research of Nadri et al. [52] shows that the empathic multimodal interface helps to improve the user experience of autonomous vehicles and users' acceptance of technology. Wu et al. [53] proposed a lightweight authenticated key agreement protocol based on intermediate fog nodes, which can resist known security attacks. Mei et al. [54] proposed a secure and effective privacy protection authentication scheme based on blockchain to provide more reliable service information for vehicle communication; These studies help users accept the multi-mode human vehicle interaction technology. Trust is the key factor for people to accept the autonomous vehicle, and multimodal interaction enhances people's trust in autonomous vehicle [55]. Sun and Zhang's findings show that synaesthesia-based multimodal interaction (SBMI) can remind people to drive more effectively [55]. The results of Arévalo et al. [56] show that multimodal interaction with physical and digital environments enhances users' flexibility and adaptability to different scenarios; users avoid switching modes frequently; when users switch modes, the user characteristics of the experience interaction and consequences affect choices more than changes in environmental conditions. Compared with traditional input methods, multimodal interaction provides users with a more natural way to operate [57].

The usability evaluation of multimodal human-vehicle interaction equipment must be considered three main aspects: (1) how to simulate human user interaction behavior, (2) multimodal human-computer interaction description based on parameters for usability analysis, (3) and evaluation of user behavior simulation, among them, the evaluation of user behavior is very important for Multimodal Dialogue in human-computer interaction (HCI). User behavior research can make the information interaction project establish and exceed the professional knowledge and expectations of designers in the process of vehicle navigation interface design [58]. Future work should evaluate whether the interaction with the system is easy to implement (i.e., interaction optimization); And the driver's understanding of the system operation [59].

6. **Conclusion.** In the concluding section, the researchers showed how to achieve the current research objectives according to the previous detailed discussion on the research results and the nature of the research.

The research introduced UTATUT-GOMS conceptual model, proposing ten causal relationships. Thirty-four items that reflect the importance of the concepts and the research variables were developed into the questionaries based on a literature review and experts' opinions, conducting a pilot study to verify the reliability and validity of the questionnaire. The population and the literature review determined the sample size. The questionnaires were delivered to the subject by hand as hard copies, and after finishing the multimodal human-vehicle interaction device operation experience, subjects filled in the questionnaires. This study uses Amos version 26.0 software and SPSS version 24.0 software to analyze the collected data. This study applied the SEM approach to testing the hypotheses. The first finding of this research was the determinant factors regarding the adoption of the multimodal human-vehicle interaction device via the literature review. Facilitating conditions, performance expectancy, effort expectancy, goals, selection rules, operations, methods, and behavioral intention. This study used these factors to investigate the user behavior of the multimodal human-vehicle interaction device. Secondly, this study evaluates SEM. This study empirically proved the ten proposed hypotheses, proving that performance expectancy, facilitating conditions, effort expectancy, goals, selection rules, operations, methods, and behavioral intention significantly positively impact multimodal human-vehicle interaction device's user behavior.

The research collected the data from a Chinese electronic company and analyzed its representativeness and employees in detail. The sampling, experimental design, experimental procedure, data collection, and data analysis strictly followed scientific experimental procedures to ensure the reliability of the research results. However, this research still has some limitations.

First, the study was conducted in China. It is suggested to conduct research in a broader range of regions and groups to compare the results. Secondly, the results of this study come from the acceptance research of the multimodal human-vehicle interaction device. Self-reported data is another limitation. The consent form clearly states that the name and agency are not included in this research. Anonymity and voluntary participation are expected to enable participants to report honestly. However, subjects may provide false information for various reasons.

Due to our research's limitations, there are some future research directions. First, this research focused on the multimodal human-vehicle interaction device, which researchers can extend to other automotive electronic technologies or devices in different fields. Secondly, this research collected data in China; researchers can study whether the findings can be extended to other regions and countries, providing richer insights into worldwide user adoption. Third, a longitudinal study is needed to investigate the dynamics of users using manual the multimodal human-vehicle interaction device.

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