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Research on Influencing Factors of Purchasing Behavior of AI Speakers in China based on the UTAUT and TTF Model

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Abstract

The purpose of this study is to explore the factors that influence the purchase of AI speakers in China. We integrate the Unified Theory of Acceptance and Use of Technology (UTAUT) and Task-technology fit (TTF) model into one model and put forward assumptions. According to the characteristics of AI speakers, we selected 6 independent variables, such as Performance Expectation, Effort Expectation, Social Influence, Facilitating Conditions, Task and Technology-characteristics. The final impact on purchase behavior is evaluated through Task-technology fit and purchase intention. After counting 478 samples, through SPSS22.0 and AMOS analysis, hypotheses have been proved by strong experimental data, except facilitating conditions. These results also imply that improving the technical level of AI speakers and enhancing consumers' purchasing intention are the central line of marketing. Based on this, we put forward several suggestions to marketers, including strengthening the research and development of AI speaker technology, and building a circle of friends of AI speakers.

Keywords : AI Speaker, Purchase Behavior, UTAUT, TTF, China

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1. Introduction

In the background of consumer upgrade, people's demands for a better family life have further increased. At the same time, the rapid rise of information and communication technologies such as 5G, big data and the Internet of Things has led to a new collision between consumer demand and technological progress. With its interactivity, home attributes and the inherent music playing function of speakers, smart speakers have become the entry point of smart home ecological construction in the era of Internet of everything.

The "Audio Product Usage Status Research Report 2020" from Qualcomm shows that smart speakers have become the most popular product in the speaker category, with the highest usage rates in the U.S., China and the U.K. [Qualcomm, 2020]. The "China 2019 Smart Speaker User Survey" published by Strategy Analytics shows that there are about 35 million households in China with smart speakers [Strategy Analytics, 2019]. But with a user size of about eighty-six million people, the market penetration rate is only 10%, much lower than the 26% in the United States. Germany, Canada, and other countries smart speaker market penetration rate is also mostly above 15% [eMarketer, 2019].

To enhance the penetration rate of the Chinese smart speaker market and give full play to the enormous potential of the Chinese market, it is very necessary for us to study what factors influence consumers to buy smart speakers, which is the purpose of this study. Smart speakers are regarded as the new entrance to connect the Internet, and the pioneer product of the development of a new generation of artificial intelligence and Internet of Things industry become the new era of hardware that took over from the smartphone. In China, the use scene of smart speakers, in addition to the home scene, is also further developing to the enterprise scene, such as offices, hotels, hospitals, nursing homes, and etc. Improving consumer acceptance and use of smart speakers has an incredibly positive effect on improving the quality of work and life and cultivating the habit of using smart products.

However, through literature reading, we found that there is no specific research on the factors influencing the purchase behavior of smart speakers, either in foreign countries or in China. In this study, we combine the Unified Theory of Acceptance and Use of Technology model and the Task-Technology fit model to form a new research model, hoping to explore more factors influencing purchase behavior at the level of "cognitive factors affecting consumers" and "task and technology".

2. Literature Review

2.1 AI Speakers

AI speaker(also called smart speaker) is an infinitely intelligent audio playback device that uses several types of connectivity (usually Wi-Fi and Bluetooth) to achieve additional functionality. Compared with traditional wireless speakers, the most important feature of smart speakers is "intelligence", which is a speaker device with voice interaction, access to web content, and web services [China Electronics Standardization Institute]. Its functions can be divided into voice interaction, content services, and Internet services. In addition, smart speakers are also considered as "intelligent home personal assistants" [Abdi et al., 2019], so it also has the role of smart home control hub.

2.2 UTAUT and TTF Model

To better predict user behavior and improve the functions not achieved by the previous model, Venkatesh et al.[2003] designed the UTAUT model with four independent variables: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating condition (FC); and four moderating variables: gender, age, experience, and voluntary use. The UTAUT model contains four independent variables: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating condition (FC); and four moderating variables: gender, age, experience, and voluntary use. They conducted an empirical study using the data and found that UTAUT could increase the explanatory power of users' behavioral intentions up to 70% using the same data. Therefore, UTAUT has been widely used to explain the adoption of mobile information systems by users since its inception [Venkatesh et al., 2003].

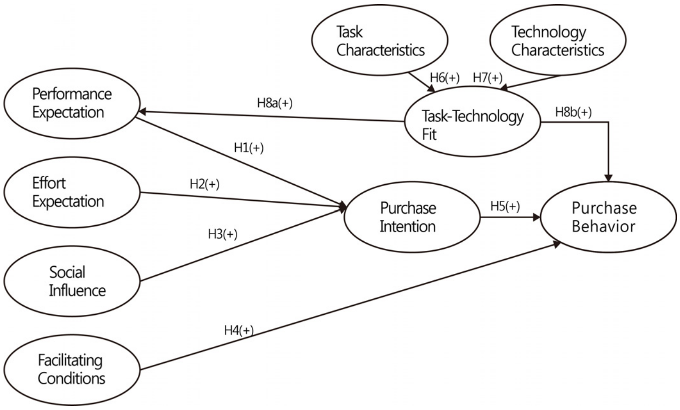
In Goodhue and Thompson [1995] article, first proposed the technology to performance chain (TPC), which argues that technology must be used and matched to its task to produce performance. In his article, he expressed the basic framework of task-technology matching theory. The experimental results verify that the value of technology depends on the tasks performed by users and that those users can evaluate the task-technology match of the technology they use. With these two studies, the task-technology matching model is formalized.

Fishbein and Ajzen [1997] consider willingness as a probability that someone will initiate a certain behavior. Dodds et al. [1991] consider purchase intention as the probability that a consumer will initiate the purchase of a certain good; Feng et al. [2006] believe that purchasing intention is the probability of consumers' purchasing behavior. The concept of consumer behavior has been evolving along with the development of economic and social development and research, as well as the different starting points of scholars in different disciplines from their background knowledge and experience in specific disciplines. according to Walters and Paul [1970], "consumer behavior is the behavioral decisions involved in people's purchase, use of products or services "; while Engel, Blackwell and Miniard [1993] redefine consumer behavior as "the activities involved when consumers consume, acquire, or dispose of a product or service, including the decisions that occur before and after these actions." Kotler [1997] argues that "the activities of individuals, groups, and organizations in selecting, purchasing, using, and disposing of products, services, ideas, and experiences to satisfy needs are consumer behavior"; the American Marketing Association (AMA)[Lei Shen, 2013] defines consumer behavior as "the relationship between perceptions The American Marketing Association (AMA) defines consumer behavior as "the dynamic interaction between perceptions, cognitions, behaviors, and environmental factors that underlie human behavior in performing the exchange functions of life".

3. Research Model and Hypotheses

3.1 Research Model

To set up the research model, integrated technology acceptance model, task technology



〈Figure 1〉 The Research Model of Purchase Behavior of AI Speakers

adaptation were employed. These two models are used to explore users' acceptance behavior, adaptability between tasks and technologies. According to the literature review in the second chapter, a research model is proposed. From the perspective of the integration of two theories, this paper discusses the influencing factors of the purchase behavior of smart speakers in China. As shown in 〈Figure 1〉.

3.2 Research Hypotheses

The research of Luo et al. [2010] shows that performance expectation is the most critical factor for people to adopt mobile banking, and Oliveira et al. [2014] also verifies that performance expectation has a positive effect on people's adoption of mobile banking. The experimental results of Wu et al. [2021] also prove the role of performance expectation in supporting the presentation of use intention. Therefore, we put forward the following assumptions:

H1: Performance expectation has a positive impact on the purchase intention of AI speakers.

Jie Chen and Zhu [2015] studied the influence of effort expectation on WeChat payment intention, and the results showed that effort expectation would positively and significantly affect users' intention to use WeChat. The assumption in [Oliveira et al., 2014] that efforts are expected to have a positive impact on purchase intention is also valid. Intention is people's judgment on whether the smart speaker is easy to use. Therefore, we put forward the following assumptions:

H2: Effort expectation has a positive impact on the purchase intention of AI speakers.

Dulle and Minishi-Majanja [2011] found that the expectation of effort is one of the key factors to obtain the intention of use. Kianayotin, Pannaruthai and Ajzen [1977] confirmed that one of the reasons why people use health IT is its ease of use. Therefore, we put forward the following assumptions:

H3: Social influence has a positive impact on the purchase intention of AI speakers.

In UTAUT theory, convenience is considered to have a direct impact on purchasing behavior [Venkatesh et al., 2003]. As confirmed in [Oliveira et al., 2014], also proved the positive role of convenience in the adoption of mobile banking. Articles [Kijsanayotin et al., 2009] confirmed that convenience significantly predicted the use of technology.

Therefore, we make the following speculation:

H4: Facilitating Conditions has a positive impact on the purchase behavior of AI speakers.

The purpose of this study is purchase behavior, so all proofs of purchase intention ultimately require that purchase intention can affect purchase behavior. According to UTAUT theory, purchase intention directly affects purchase behavior [Venkatesh et al., 2003]. Fishbein and Ajzen [1977] and others concluded that the influence of willingness to use on use behavior is much higher than other antecedents. The research data in [Oliveira et al., 2014] also shows that behavioral intention has a strong influence on behavioral adoption. Therefore, we put forward the following speculation:

H5: The purchase intention of AI speakers has a positive influence on the purchase behavior.

Just like the article [Wu et al., 2021] verified that the task characteristics and technical characteristics of transnational payment have a positive effect on task technology matching, and thought that only when the task technology matches, can information technology play the greatest role. Article [Oliveira et al., 2014] also verified that the task features and technical features of mobile banking have a positive effect on the matching of task technologies, and thought that how to match the characteristics of task and technology can lead to the coincidence of higher-level tasks and technologies. Ling et al. [2020] thinks that a technology product can help people accomplish four tasks, which are communication, information transmission, entertainment and payment transaction. The more types of tasks a single technology product can accomplish, the higher the degree of task technology adaptation.

Therefore, we put forward the following assumptions:

H6: The task characteristics of AI speakers have a positive impact on task technology matching.

H7: The technical characteristics of AI speakers have a positive impact on task technology matching.

Article [Oliveira et al., 2014] thinks that users can meet the expected expectations from the functions of mobile banking, and this is confirmed by experimental data. Article [Ling et al., 2020] believe that AI speakers can help people from both entertainment and daily information transmission. For example, listening to music, audio books, chatting and interacting, playing traffic and weather information, etc. If these two functions can adapt to the user's task requirements faster, it can complete the task faster. Wang et al. [2020] thought that if the task technology could not be matched, consumers would not adopt this technology. At the same time, this paper also assumed that the matching of task technology would positively affect the purchasing behavior of healthcare wearable devices. Zhou et al.[2020] assumed and verified that task technology matching has a significant impact on the adoption of mobile banking. Compared with traditional speakers, AI speakers have more advantages in both entertainment and information transmission. The performance expectation in this study is that consumers think AI speakers can improve the convenience of life. Therefore, we put forward the following assumptions:

H8a: Task technology fit has a positive impact on performance expectations.

H8b: Task-technology fit has a positive impact on the purchase behavior of AI speakers.

4. Empirical Results

4.1 Data Collection and Sample

This study collects data through questionnaire survey. Because our research is aimed at the first purchase behavior, our main survey object is people in Chinese mainland who have never bought and used AI speakers before. After the investigation, we used structural equation model (SEM) to analyze large samples. Generally speaking, the total number of SEM samples should be more than 200 to ensure the accuracy of the results [Kline, 2021]. In factor analysis, variables are described by 3-5 items. The optimal size of the predicted sample is five times that of the items in the scale. If the sample size reaches 10 times of the project, the result will be more stable. In this paper, there are 8 variables, 43 measurement items and 478 valid samples. The sample size is about 11 times of the number of projects, which meets the requirements of SEM for sample size. We sent out an online questionnaire through Questionnaires (http://www.wjx.cn), collected 573 questionnaires, and screened out 478 valid questionnaires (the effective questionnaire rate was 83.4%) by classifying and evaluating the questionnaires. We put the first part about personal information in ⟨Table 1⟩.

According to the research requirements of structural equation model, when there is more than one research variable in the model, each research variable must have at least three observation variables. According to the previous research results, we have formed the measurement project of this paper. (1) six independent variables (Performance Expectation, Effort Expectation, Social Influence, Facilitating Conditions, Technology Characteristics, Task Characteristics), (2) two intermediate variables (Task-Technology Fit, Purchase Intention), (3) one dependent variable (Purchase Behavior).

⟨Table1⟩ Demographic Characteristics of the Sample

	Category	Percentage
Gender	Male Female	46.86% 53.14%
Age	⟨20 20-25 26-35 36-45 ⟩45	7.11% 34.1% 36.61% 15.48% 6.69%
Region	North China Northeast China East China Central China South China Southwest China Northwest China	7.53% 6.9% 46.23% 26.36% 5.86% 3.97% 3.14%
Education	High School and below College and University Master Doctor	4.81% 54.6% 25.52% 15.06%
Monthly Income (CNY)	⟨5000 5001 - 10000 10001-15000 ⟩15000.	44.14% 33.47% 12.13% 10.25%

The questionnaire was measured by a seven-point Likert scale, ranging from "strongly disagree", " disagree", " somewhat disagree "," neutral", " somewhat agree", " agree", "strongly agree".

4.2 Analysis of Reliability and Validity

Reliability test is an important link to ensure the quality of the questionnaire. In this study, SPSS22.0 was used to test the reliability. The total Cronbach's α coefficient is 0.970, which is greater than 0.7. At the same time, we also evaluated Cronbach's α coefficient of each variable, and the results are shown in Table2. According to the data in the table, Cronbach'sα values of all variables are greater than 0.7, which indicates that the scale has high reliability.

〈Table 2〉 Cronbach's α coefficient and CITC values of each variable

Variables	Items	CITC value	Cronbach's α if Item Deleted	Cronbach's α
Performance Expectation	PE1	0.746	0.865	0.891
	PE2	0.709	0.881	
	PE3	0.770	0.857	
	PE4	0.823	0.837	
Effort Expectation	EE1	0.707	0.828	0.863
	EE2	0.802	0.788	
	EE3	0.752	0.810	
	EE4	0.595	0.873	
Social Influence	SI1	0.693	0.844	0.869
	SI2	0.782	0.807	
	SI3	0.829	0.789	
	SI4	0.593	0.880	
Facilitating Conditions	FC1	0.637	0.842	0.853
	FC2	0.742	0.794	
	FC3	0.731	0.800	
	FC4	0.681	0.819	
Task Characteristics	TaskC1	0.726	0.890	0.904
	Task C2	0.821	0.872	
	Task C3	0.819	0.870	
	Task C4	0.819	0.870	
	Task C5	0.643	0.912	
Technology Characteristics	TC1	0.617	0.869	0.890
	TC2	0.769	0.859	
	TC3	0.830	0.847	
	TC4	0.694	0.879	
	TC5	0.817	0.851	
Task-Technology Fit	TTF1	0.805	0.875	0.905
	TTF2	0.653	0.906	
	TTF3	0.698	0.900	
	TTF4	0.821	0.872	
	TTF5	0.853	0.866	
Purchase Intention	PI1	0.652	0.900	0.863
	PI2	0.791	0.762	
	PI3	0.793	0.763	
Purchasing Behavior	PB1	0.780	0.831	0.880
	PB2	0.787	0.829	
	PB3	0.744	0.846	
	PB4	0.663	0.880	

〈Table 3〉 The Correlation coefficient and discriminant validity

Variables	one	two	three	four	five
1. Effort Expectation	0.628 (0.792)				
2. Social Influence	0.602	0.654 (0.808)			
3. Facilitating Conditions	0.724	0.799	0.593 (0.770)		
4. Task Characteristics	0.63	0.677	0.778	0.669 (0.817)	
5. Technology Characteristics	0.629	0.755	0.764	0.915	0.617 (0.785)

If the correlation coefficient of variables is less than the square root of AVE value, it can be said that the discriminant validity is achieved. As shown in 〈Table 3〉 in this study, the correlation coefficient between effort expectation, task-characteristics and technology characteristics is too high, indicating that task-characteristics and technology characteristics can be combined into one. On the other hand, the correlation coefficients of other variables are all less than the square root of AVE value, which can be said to be effective.

4.3 Hypotheses Test Results

AMOS22.0 tests the hypothesis of the research model and analyzes the influence intensity and significance of each path on the factors influencing the purchase behavior of AI speakers. The results are shown in 〈Table 4〉.

H1 was supported. The standardized coefficient between performance expectation and purchase intention is 0.36, with a significant level p 〈 0.001, which indicates that performance expectation has a positive im-

〈Table 4〉 The Results of hypotheses test

Hypothesis	Estimate	Standardized Coefficients	S.E.	C.R.	P-value	Supported or Not Supported
H1: PE→PI	0.316	0.36	0.041	7.666	0.000	Supported
H2: EE→PI	0.373	0.328	0.06	6.167	0.000	Supported
H3: SI→PI	0.269	0.242	0.059	4.689	0.000	Supported
H4: FC→PB	0.056	0.049	0.046	1.229	0.219	Not Supported
H5: PI→PB	0.897	0.772	0.061	14.633	0.000	Supported
H6: TaC→TTF	0.183	0.154	0.091	2.006	0.045	Supported
H7: TC→TTF	0.946	0.803	0.108	8.772	0.000	Supported
H8a: TTF→PE	0.684	0.706	0.043	15.834	0.000	Supported
H8b: TTF→PB	0.247	0.25	0.039	6.411	0.000	Supported

$^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

Note: PE(Performance Expectation), PI(Purchase Intention), EE(Effort Expectation), SI(Social Influence), FC(Facilitating Conditions), PB(Purchasing Behavior), TaC(Task Characteristics), TTF(Task-Technology Fit, TC(Technology Characteristics) pact on purchase intention.

H2 is supported. The standardized coefficient between effort expectation and purchase intention is 0.328, significant level P 〈 0.001, indicating that effort expectation has obvious positive influence on the purchase intention of AI speakers, and simple and easy-to-learn operation can directly attract consumers.

H3 is supported. The standardized coefficient between social influence and purchase intention is 0.242, with a significant level P 〈 0.01, indicating that community influence also has a positive impact on purchase intention. When important family members and friends around have a good evaluation of a certain AI speaker, it is more conducive to promoting consumers to buy the same brand or model of AI speakers.

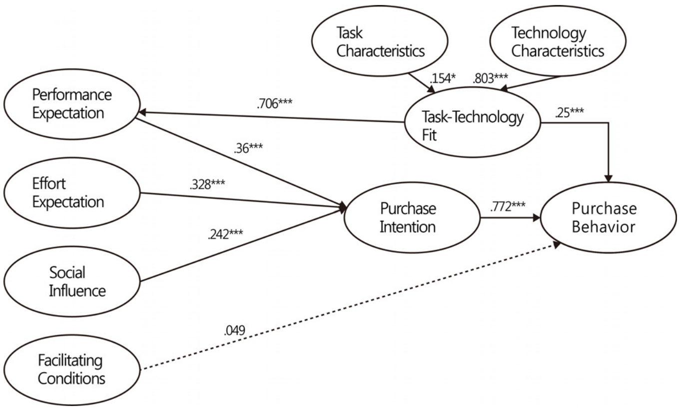
H4 was not supported. The standardized coefficient between facilitating conditions and purchase intention is 0.049, and the significant level P=0.219, which shows that convenience has no positive influence on the purchase intention of AI speakers.

H5 received support. The standardized coefficient between purchase intention and purchase behavior is 0.772, with a significant level P〈0.001, which indicates that purchase intention has a positive impact on purchase behavior. For marketers, grasping several variables that influence purchase intention will definitely have a positive impact on the final result.

H6 is supported. The standardization coefficient between Task characteristics and Task-technology Fit is 0.154, with significant level P〈0.05, which indicates that Task characteristics have certain influence on Task-technology Fit. The more tasks that AI speakers can perform, the stronger the matching between tasks and technologies, which will directly prompt consumers to purchase.

H7 is supported. The standardization coefficient between Technology Characteristics and Task-technology Fit is 0.803, and the significant level is p〈0.001, which indicates that technology characteristics have a very positive impact on Task-technology Fit. The more comprehensive and advanced the technology contained in AI speakers, the more tasks they can accomplish, and the better the consumer's experience.

H8a is supported. The standardized coefficient between Task-technology Fit and performance expectation is 0.706, with a sig-



〈Figure 2〉 Result of Hypotheses Test

nificant level P<0.001, which indicates that task technology adaptation has a positive impact on performance expectation. In fact, this shows from another aspect that technology is the core driving point for consumers to buy AI products.

H8b was supported. The standardized coefficient between Task-technology Fit and purchasing behavior is 0.25, with significant level P<0.001, which indicates that task technology adaptation has obvious positive influence on purchasing behavior. It also shows that we should concentrate on improving the key technology level and take technology as the focal point of marketing.

5. Conclusions

Through the application of integration technology acceptance theory in the field of AI speakers, the empirical results show that performance expectation has a positive impact on purchase intention, and the impact is significant. This study shows that consumers' purchase intention depends on whether the convenience of life is improved and whether AI speakers are extremely useful for life. Only when more consumers feel that AI speakers are useful to their lives will they be more active in purchasing them. We also verified that performance expectation, effort expectation, and social influence. AI speakers' purchase behavior by affecting purchase intention. These dimensions are closely related and inseparable. Expectations are key. People usually need to have a clear understanding of how much they need to pay and how much they can get out of a thing. Especially for help products like artificial intelligence speakers, if the operation is troublesome and the help obtained is unsatisfactory, then consumers' desire to buy must be low, and it needs a simple and convenient operation process and satisfaction beyond expectation to make consumers have a valuable experience.

The social impact is very direct. In Chinese society and culture, this characteristic should be even stronger. Consumers are far more receptive to the opinions of those around them than AI speaker salespeople and advertising. We verify the direct influence of Task-Technology Fit theory on AI speaker purchasing behavior, and the direct influence of Task-Technology Fit factors on performance expectation. The technology problem of AI speakers is the focus of this research. Intelligent technology is the core of other intelligent products such as AI speakers, and it is also the decisive factor that affects marketing. The experiment shows that consumers' purchase behavior is strongest when the technology and task are highly matched, that is, the task technology is highly matched.

Our research model also proves that the community relationship is an important influence factor on the purchase intention of AI speakers, so building an "AI circle of friends" can be an important incentive to attract consumers to buy. Because of the influence of family or friends around you, you can form a community with them after purchase, and share information and favorite content through AI speakers, which will undoubtedly increase the attractiveness of purchase, improve the use efficiency after purchase, and enhance user activity. The essence of AI speaker is voice interaction, which is composed of three parts: Automatic speech recognition, Natural language processing and Text-To-Speech, equivalent to process of encoding-decoding-outputting" often said in human language. They are a whole, called the "troika" of the voice interaction process. The current AI speaker speech recognition accuracy is low, and there are often scenes that cannot recognize the meaning of human voice, The consumer experience is not good. At the same time, there will be many inconveniences, such as the inability to talk continuously, too long wake-up words (four-word wake-up words are inconvenient) and the need to mention them repeatedly.

There are some shortcomings and limitations in this study due to the limitations of time, energy, and research capacity. Some issues involved in the study have not been explored in depth, and we hope to further deepen the study in the future. In the future research, we can conduct in-depth interviews with AI buyers and potential buyers to improve the pertinence and accuracy of the research. And we can strengthen the research on four adjustment variables, which will make the research of integrated technology acceptance theory in the field of AI speakers more profound and accurate. In the next research career, researchers will devote themselves to combining digital marketing theory with communication theory to study more new ideas and methods in the field of AI products.

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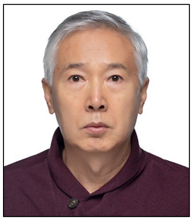

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