Factors Influencing the Acceptance and Usage of Smart City Services: A Systematic Review and Meta-analysis

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Abstract. Smart city services and applications have gradually come into the life of citizens. Citizens' use of smart city services is necessary for the sustainable development of such services. However, the existing literature has a large difference in research conclusions on the relationship between smart city service user behaviors and their influencing factors. In this paper, the meta-analysis method was used to review 54 independent samples in 52 studies, the related effects of 33 influencing factors were analyzed. The meta-analysis results show that 31 influencing factors have significant effects on the adoption, use, and continuance behaviors of smart service users. In addition, sample groups have a moderating effect on the relationship between user behaviors and variables such as social influence. This paper has clarified the effects of influencing factors and one moderator, which has a certain reference value for improving the use intention and participation of users of smart services and applications.

Keywords: Smart city · Mata-analysis · User behaviors

1 Introduction

Victor Mayer Schoenberg, author of Big Data Age, points out that the information storm caused by big data is transforming our life, jobs, and thinking. The great value generated by big data is being recognized by people. It provides a new way of looking at the world through technological innovation and development, as well as the comprehensive perception, collection, analysis, and sharing of data. Therefore, scientist Andreas Weigend said, "data is the new oil".

Big data is the general term for a very large system. The development and wide application of ICT has brought convenient services to people's travel and life, and also promoted the progress of cities. In recent years, with the development of Internet of Things, cloud computing and mobile Internet, modern digital and network-based cities are moving towards automated and smart cities [1]. Smart city is a strategic issue that many countries in the world have focused on in recent years, and it is regarded as an important means to solve urban development problems, improve people's livelihood, and enhance competitiveness of a city.

N. Streitz and S. Konomi (Eds.): HCII 2020, LNCS 12203, pp. 477–490, 2020.
https://doi.org/10.1007/978-3-030-50344-4_34

Smart social applications and services have incorporated massive data based on emerging technologies, transmit processed and integrated information of city. They are important carriers to connect smart society and citizens and can help achieve rational allocation and intelligent response of urban resources [2], with the characteristics of real-timeliness, mobility, integration, etc., covering government affairs, transportation, home services, energy, medical and other fields. By providing citizens with a variety of real-time mobile online services such as urban transportation, health care, and government affairs guidance, smart services can assist urban governance and improve citizens' quality of life. Therefore, they have great practical significance in addressing urban problems and a series of social and livelihood issues, enhancing competitiveness of a city, etc [3].

In addition to urban construction and governance, various smart services and applications in the fields of transportation, medical care, energy, public security, construction planning and education (such as Smart Community Comprehensive Information O2O Service Platform, "Cloud Health" Service Platform, Smart Parking Systems, etc.) also require the active participation of citizens and users [4]. The research by Chourabi et al. indicated that related technical factors (e.g. service stability, system security and data integration), organization and users are key factors for the success of smart city services [5]. Peng et al. pointed out in the case study of the British smart parking system that the government should decide on the selection, implementation and deployment of smart city services based on the actual needs of potential users, namely local residents [3]. Many user-related factors (e.g. user information literacy, user awareness, public acceptance, user participation, etc.) will affect the final results and effects of smart city service implementation.

From different theoretical perspectives, scholars have done a lot of research on the adoption, use behavior and intention of the users of smart services and applications such as wearable medical devices, smart home services, and smart government, etc. to explore the factors influencing user behaviors. However, previous studies differ widely in their conclusions. In addition, previous research didn't fully explore into the following problems:

- What are the attributions of user behaviors in smart services and applications in different fields?
- Is there any difference in influence strength?
- Will different research conclusions be caused by different subject groups?

Therefore, it is necessary to systematically review and integrate existing literature in order to draw a comprehensive and universal research conclusion.

Based on the above research gaps, this study focuses on the use intention and behavior of smart services and applications, and adopts the meta-analysis method to quantitatively analyze the factors that influence the behaviors of smart service users, comprehensively evaluates the strength of the relationship between the use of smart services and various influencing factors, and explores the moderating effects of the types of smart services and applications and the sample population characteristics, with a view to promoting the implementation and improvement of smart city applications and services from the micro perspective of use, providing support for decision making in smart city construction and development.

2 Literature Review

The research on smart services and applications is mainly focused on the following three aspects:

- Mobile APP development, focusing on smart city mobile services and application design [6, 7];
- Exploring the barriers and obstacles in smart city APP promotion based on social background and local policies [8, 9];
- Analyzing the users' adoption behavior and related influencing factors based on existing theoretical models in the field of information systems [9, 11].

Focusing on the user behaviors of smart services and smart devices, scholars have explored the factors that affect user intention and behavior from the aspects of adoption, use, and continuance.

In terms of adoption intention and behavior, literature suggests that user perception factors are major factors affecting users' intention to use smart services. Users are likely to adopt a smart service or smart device only when they perceive such a need [12]. In addition, some scholars have analyzed factors such as demographic characteristics and environment. Taking the fields of smart medical care as example, in addition to user perception factors such as perceived usefulness, perceived ease of use and privacy concerns, users' technical acceptance intention is also moderated by demographic factors such as age, gender, and educational level [13]. Besides, external factors such as social influence and cost, and platform system factors such as service quality and system quality also have significant effects on user adoption behavior and intention [14].

The research on use behavior and intention of smart service and application users has been conducted from multiple theoretical perspectives. For example, Klobas et al. used Reasoned Action Theory to conduct research on users' intention to use smart home devices from the aspects of perceived security risk and perceived controllability [15]. In addition, from the perspective of Innovation Diffusion Theory, some studies have discussed the influence of relative advantage, observability, complexity, compatibility, trialability and other innovative attributes of smart services on the use intention and behavior of users [16]. Some other research built a theoretical framework using information resources, management services, platform technology, and equipment effectiveness and other system factors and service factors as core variables by reference to the Delone and McLean Model of Information Systems Success (D&M Theory), and the research fields covered smart communities, smart medicine, smart transportation, etc. [17]. The theoretical foundations involved in the research on use intention and behavior also include the Value-based Adoption Model [18], Social Cognition Theory [14], transaction cost theory [19], and motivation theory [20], etc.

The continuance behavior has been a focus of researches in the field of information systems. In terms of smart services and applications, however, there are not much research literature on users' continuance intention and behavior, and they mostly focus on smart government services, smart tourism, and smart life services and applications. Among them, most of the literature analyzes the factors that influence users' continuance intention and behavior from the aspects of intrinsic motivation (including user perception dimensions such as satisfaction, privacy concerns, and expectations confirmation) [21] and extrinsic motivation (including system and environmental factors such as service quality, cost of use, and social support) based on the continuance theory [22].

By sorting out the existing literature on user behavior of smart services and applications, it can be seen that empirical researches have been conducted on the motivation of smart applications and services. However, there has been no paper that comprehensively evaluates the factors that affect the user behaviors of smart services and thus no comprehensive and universal conclusion. At the same time, due to different sample sources, sample sizes, methods and models, and research perspectives, existing studies on user behavior in the context of smart cities have significant differences in the aspects of research field, research conclusion, test subjects, and theoretical basis. The differences include:

- Different natures of influencing factors. Taking the research on the users' intention to adopt smart meters as an example, based on TAM theory, Zamrudi et al. pointed out that perceived ease of use can significantly increase users' intention to adopt smart meters [23]. However, Wunderlich et al. believed that users have no in-depth interactive use of smart meters, so perceived ease of use is not important for users' intention to adopt smart meters; and internal and external incentives are the key factors affecting their intention to adopt [24].
- Different strengths of influencing factors. For example, research by Yuen et al. showed that reliability has almost no influence on the user behavior of smart express cabinets ($r = 0.08$) [19]. Park et al. found that there was a weak correlation between system reliability and users' intention to use smart home devices ($r = 0.289$) [20]. However, Sepasgozar et al., based on social cognition theory, pointed out that technical reliability can significantly affect the use of smart city service technology ($r = 0.660$) [14].
- Different research subjects. Most of the studies are targeted at users of their respective smart service and application, but some are targeted at special populations such as the elderly. Whether the difference in demographic characteristics affects the influencing strength of various factors needs to be explored to test its moderating effects.

This study uses a Meta-Analysis method to quantitatively analyze the factors influencing user behaviors of smart city services, quantify and merge the research results of existing literature, to solving the problem of different research conclusions in existing literature and providing a more objective conclusion for the research on user behaviors in the context of smart city.

3 Methodology

Meta-analysis is an empirical research method for statistical analysis of a large number of independent research results. It can draw a more universal conclusion from multiple similar research results under the same topic. It is a secondary comprehensive analysis and evaluation of existing research literature and has a more convincing conclusion than a single research. Trahan [25] and Salang [26] discussed Meta-Analysis in the field of information systems early; Ankem then introduced in details about how to use Meta-Analysis in the field of information management, and discovered that there had been extremely limited applications of meta-analysis in the field of library and information [27]. The application of meta-analysis mainly includes two aspects. 1) Meta-analysis can be used to obtain the weighted average effect value of different study results to check the strength of the relationship between two variables; 2) Meta-analysis can be used to explore the moderating effects of factors such as research scenarios and research objects on the relationships between variables [28].

Meta-analysis provides an effective method for unifying academic differences. The specific steps of the Meta-Analysis include:

- Extensively search for empirical research results of specific research subject;
- Select research results and based on a predetermined set of transparent literature selection criteria to form a database;
- Perform comprehensive analysis using specific statistical analysis techniques and calculate the accurate effect value [29].

According to the characteristics of meta-analysis, this paper conducts research in accordance with the process of literature search and screening, literature coding, analysis of influence factors, analysis of moderating effects, and interpretation of results.

3.1 Collection and Selection of Publications

The publications collection in this paper was carried out jointly by two researchers, and the search results were compared and supplemented. Search platforms used included English databases such as Web of Science (SCIE, SSCI, ISTP, ISSHP), EBSCO, Taylor & Francis Online and ProQuest Dissertations & Theses (PQDT) Full Text, PsycInfo, SAGE Journals Online, Springer, and Elsevie Science. The keywords "smart city", "smart service", "IoT", "wearable technologies", "smart library", "smart home", "smart devices", "AI" were matched with "user", "user behavior", "usage", "Behavior", "adopt", "adoption", "accept", "continuance", etc. for search in the databases for English literature.

The publications retrieved were sorted according to the following criteria:

- The papers must be empirical research on the users behaviors or intention to use smart applications or smart services, excluding qualitative research papers such as review research, theoretical research and case research.
- The papers clearly report the sample size, the coefficient r of correlation between user behavior, intention and related influencing factors, or t, p, or F value that can be used to calculate such correlation coefficient.

In addition, we checked references in review papers and empirical research papers to avoid missing relevant references. In the end, 52 publications suitable for meta-analysis were obtained, two of which contained two independent samples each, so there were a total of 54 independent samples; the total number of subjects reached 17,407.

3.2 Coding and Analysis Process

This study adopted coding procedure recommended by Lipsey and Wilson [30]. In order to reduce the occurrence of coding errors, two researchers first compiled a coding manual and coding instructions, which were discussed with other two researchers and modified before used as the reference basis for coding. The main information of the coding manual includes two parts. One is the basic information of the literature, including author publication date, publication platform, topic, subjects, research object, research field, theoretical basis and other research characteristics. The other is the effect value, including sample size, influencing factors and their effect value *r* or regression coefficient *t*, etc.

Each independent sample is used as a coding unit. If a paper contains multiple independent samples, they will be coded separately. At the same time, moderators were tested, so the samples were grouped according to the moderators during the coding process. After each paper was coded, a certain number of papers were randomly selected and coded by another researcher to ensure the accuracy of the coding. For those inconsistent contents, a consensus was reached through backtracking and discussion. The coding results of some papers are shown in Table 1.

Independent variables with frequency of 3 or more were selected based on behavior theme for Meta-Analysis. Among them, the adoption, use, and continuance intentions had 7, 3, and 23 influencing factors respectively suitable for meta-analysis.

Referring to the meta-analysis method and steps proposed by Lipsey and Wilson, this review uses the correlation coefficient r as the effect value. Some papers do not report r, but reported P, t. These coefficients must be converted into correlation coefficient r. The entire Meta-Analysis calculation process was performed by the software CMA 2.0 (Comprehensive Meta-Analysis 2.0). For effect value test, the software first weighted the r value according to the sample size, and then converted it into related indicators such as Fischer Z; finally, they were calculated to obtain the final correlation coefficient, confidence interval and variance, etc., and whether to use a fixed effect model or a random effect model was determined based on the result of the heterogeneity. The fixed effect model assumes that all samples originate from the same population, so it applies to homogeneous meta-analysis results; the random effect model assumes that each sample comes from a different population, and there are differences between different studies, so it applies to heterogeneous meta-analysis results.

4 Findings

4.1 Correlation Effect Analysis

Table 2 shows the meta-analysis results on relationship between adoption, use and continuance behaviors and intention of smart service and application users and some of their influencing factors.

In this study, the analysis of publication bias was performed using the fail-safe number method. Rosenthal et al. pointed out that there is no publication bias when the value of the fail-safe number N is greater than 5 * the number of studies K + 1031. Publication bias refers to that in academic research, empirical studies with conclusions showing

Table 1. Publications coding table (part)

No.	Author (Year)	Behavior theme	Sample size	Subjects	Research object	Field	Theoretical basis	Influencing factors (effect value)
1	Pal D. et al. 2018	Intention to use	239	Elderly	Healthcare Home System	Smart medicine	UTAUT	Perceived Trust (0.653), Facilitating Conditions (0.474), Social Influence (0.586), Technology Anxiety (−0.620), Perceived Cost (−0.730), Effort Expectancy (0.692), Performance Expectancy (0.677), Expert Advices (0.416)
2	Yang H., Lee H., Zo H. 2013	Intention to use	216	Citizens	Smart home services	Smart home	TPB Theory	Automation (0.589), Mobility (0.625), Inter-operability (0.611), Privacy Risk (−0.323), Physical Risk (−0.168), Trust in service provider (0.555), Attitude (0.691), Subjective Norm (0.693), Perceived Behavioral Control (0.556)
3	Baudier P., Ammi C., Rouchon M. D. 2018	Intention to use	316	Students	Smart home device	Smart home	UTAUT TAM2	Safety Security (0.465), Health (0.505), Convenience Comfort (0.591), Sustainability (0.446), Performance Expectancy (0.663), Effort Expectancy (0.426), Social Influence (0.421), Hedonic Motivation (0.513), Price Value (0.469), Habit (0.725), Personal Innovativeness (0.493)
4	Nascimento B., Oliveira T., Tam C. 2018	Continuance intention	574	Common citizens	Smart watch	Smart life	Continuance Theory	Habit (0.64), Perceived Usefulness (0.59), Confirmation (0.42), Perceived Usability (0.44), Perceived Enjoyment (0.44), Satisfaction (0.62)
5	Li H. et al. 2016	Adoption behavior	333	Common users	Wearable medical device	Smart medicine	Privacy Calculus	Information Sensitivity (−0.221), Personal Innovativeness (0.211), Legislative Protection (0.145), Perceived Prestige (0.209), Perceived Informativeness (0.253), Functional Congruence (0.252), Perception Privacy Risk (−0.251), Perceived Benefits (0.315)

Table 2. Meta-analysis results on the of relationship between smart service and application user behaviors, intention and some influencing factors

Behavior	Influencing factor	Model	K	Sample size	Point estimate	Z value (2-tail)	95% interval	Q value	$df(Q)$	I^2	Fail-safe number N
Adoption	Trust	Fixed	6	1759	0.274	11.751	0.230–0.317	53.538	5	90.661	202
		Random			0.286	3.588	0.133–0.425				
	Social influence	Fixed	5	1908	0.469	22.154	0.433–0.504	122.98	4	96.747	746
		Random			0.626	4.924	0.415~0.733				
	Perceived privacy risks	Fixed	6	2694	−0.288	−15.332	−0.322~−0.253	79.818	3	93.736	392
		Random			−0.379	−4.592	−0.515~−0.225				
Continuance	Expectation confirmation	Fixed	3	1139	0.511	18.965	0.467–0.553	21.159	2	90.548	284
		Random			0.531	5.875	0.375–0.658				
	Satisfaction	Fixed	3	1139	0.655	26.336	0.620–0.687	8.883	2	77.486	528
		Random			0.660	12.129	0.581–0.726				
Use	Service quality	Fixed	4	1372	0.371	14.356	0.324–0.416	165.144	2	98.183	223
		Random			0.395	2.05	0.018–0.673				
	Convenience	Fixed	6	1814	0.472	21.751	0.436–0.508	171.121	5	97.078	735
		Random			0.476	3.740	0.241–0.658				
	Perceived usefulness	Fixed	13	4740	0.58	43.375	0.560–0.598	299.364	12	95.992	6375
		Random			0.569	8.731	0.463–0.659				

a significant correlation are more likely to be published than those with conclusions showing no significant correlation. Therefore, the results are more representative if the Meta-Analysis has no publication bias. According to the Meta-Analysis results, there is publication bias in the adoption behavior and intention influencing factor age (N = 16), and the use behavior and intention influencing factors technicality (N = 0), affordability (N = 6), and privacy concerns (N = 35), and other influencing factors passed the publication bias test.

The heterogeneity test is mainly to determine the model of Meta-Analysis. In the Meta-Analysis results, the Q value, df (Q), and its significance test value p are used to indicate the heterogeneity between the effect sizes. Taking the effect value of use influencing factor perceived usefulness as an example, the Meta-Analysis results show that the Q value is 299.365 (df = 12, p = 0.000), and it is significant, indicating that heterogeneity among the effect values. Excluding the 4 independent variables with publication bias, for the remaining 29 independent variables, the Q values obtained in the heterogeneity test are much greater than df (Q), and all p values are less than 0.001, indicating high heterogeneity in the effect values. Therefore, a random effect model is selected for effect value analysis.

According to the point estimated effect value in the random effect model, there is no significant correlation between age and adoption behavior and intention ($r = -0.076$, $p = 0.366$); among the influencing factors of use behavior and intention, affordability ($r = 0.166$, $p = 0.661$), privacy concerns ($r = -0.162$, $p = 0.382$), and technicality

Table 3. Correlation between behaviors and intention of smart city service and application users and their influencing factors

Behavior theme	Correlation	Influencing factors
Adoption behavior and intention	Strong $r > 0.5$	Social influence, Perceived usefulness, Perceived ease of use
	Average $0.3 < r < 0.5$	Trust, Personal innovation, Perceived privacy risk (negative correlation)
Use behavior and intention	Strong $r > 0.5$	Self-efficacy, Performance expectancy, Trust, Compatibility, Habits, Perceived value, Practicality, Enjoyment, Perceived ease of use
	Average $0.3 < r < 0.5$	Hedonism, Reliability, Economic value, Service quality, System quality, Effort expectancy, Social influence, Convenience, Perceived usefulness, Perceived risk (negative correlation), Personal innovation
	Weak $0.1 < r < 0.3$	Perceived cost
Continuance behavior and intention	Strong $r > 0.5$	Perceived usefulness, Satisfaction, Expectation confirmation

(r = −0.105, p = 0.774) have no significant effects on the use behavior and willingness of smart city service users. Other influencing factors all have different degrees of correlation with user behavior and intention. According to Cohen's criteria for dividing the strong and weak effect values [32], the correlations between different behavior themes and their influencing factors were divided according to the strength, as shown in Table 3.

4.2 Moderating Effect Analysis

This paper examines the moderating effect of the subjects on the relationship between user behaviors and intention and their influencing factors. Specifically, if the groups pass the heterogeneity test, it means that the research on different groups has different characteristics, indicating significant moderating effect. In view of the limited number of studies, user behavior themes were not grouped for moderating effect test; instead, the subjects and smart areas were grouped, and the influencing factors were selected from each group in which the number of studies (k) is greater than or equal to 2 for meta-analysis. Based on the above conditions, the factors social influence, convenience and performance expectancy were selected for the moderating effect analysis. Due to their limited number of empirical studies, other influencing factors were not included in this analysis to ensure the reliability of Meta-Analysis result. Table 4 shows the analysis results of the moderating effects of subjects on the relationship between the user behavior, intention and some influencing factors under the random effect model.

Table 4. Results of analysis on the moderating effect of subjects

Moderator	Heterogeneity			Group	K	Sample size	Effect size and 95% interval		Test of null (2-tail)	
	Q value	Df (Q)	P value				Point estimate	95% interval	Z value	P value
Social influence	6.176	2	0.046	Elderly	2	537	0.594	0.536–0.646	15.751	0.000
				Students	4	1077	0.410	0.222–0.569	6.422	0.000
				Common users	11	3980	0.487	0.354–0.601	4.063	0.000
Performance expectancy	6.853	2	0.037	Elderly	2	569	0.636	0.577–0.688	15.708	0.000
				Students	4	1077	0.51	0.304–0.669	4.449	0.000
				Common users	5	972	0.515	0.426–0.594	9.738	0.000
Convenience	46.890	2	0.000	Elderly	2	569	0.522	0.433–0.600	9.882	0.000
				Students	2	398	0.084	0.354–0.693	4.953	0.000
				Common users	5	1713	0.546	−0.015–0.181	1.671	0.095

According to the heterogeneity test results, the subject group has a significant moderating effect on the relationship between convenience and user behaviors (Q = 46.890, p = 0.000). The convenience can positively affect the elderly and common users' use of and intention to use smart city services, and the effect values of two groups have no significant difference. However, for the student group, there is no significant relationship between this independent variable and user behaviors (r = 0.084, p = 0.095).

The subject group has a certain impact on the relationship between social influence (Q = 6.167, p = 0.046), performance expectancy (Q = 6.853, p = 0.037) and the smart city service user behaviors, with less significant moderating effect than convenience.

Specifically, the social influence has a more significant effect on the smart service use behavior and intention of the elderly group, showing a strong correlation (r = 0.594), followed by the common user group (r = 0.487) and the student group (r = 0.410). For performance expectancy, it shows different strengths of impact on different groups of subjects. Similar to social influence, performance expectancy shows the most significant effect on the behaviors and intention of smart service users in the elderly group (r = 0.636), and has almost similar effects on common users (r = 0.510) and student groups (r = 0.515).

5 Discussion and Conclusion

5.1 Adoption

This study has identified the influencing factors in the adoption, use, and continuance stages of smart service users through coding analysis of existing literature, and obtained the effect values of the influencing factors on user behaviors and intention, classified the influencing factors according to their correlation significance. In this paper, based on the correlation strength evaluation criteria proposed by Cohen, we found that perceived usefulness (0.696), social influence (0.626), and perceived ease of use (0.568) are the three most important factors influencing the adoption behavior and intention of smart service users, the following are personal innovation (0.444), personal privacy risk (−0.379), and trust (0.3). It indicates that the users' emotional perception factors play an important role in the adoption of smart city services.

However, age has no significant influence on the adoption behavior and intention of smart city service users. This meta-analysis result is contrary to traditional cognition. In previous research assumptions, the elderly group was mostly considered to have low intention to adopt new technologies due to limited information literacy. However, with people's deepening understanding of smart city technology in modern society, as well as the more unified and user-friendly functions of smart services and mobile APP's UI design, demographic factors such as age and gender longer play an important role in the adoption of smart services and smart technologies.

5.2 Use

Different from the adoption behavior, platform factors such as compatibility, practicality, service quality, and system quality can also significantly affect the use behavior and intention. This is related to the behavior stages of users. After a user has used the smart service for a period of time, his focus will shift from the initial psychological cognition to system and platform services. Therefore, compatibility, practicality, reliability and other platform functional characteristics will play an important role in the stage of use.

Some personal characteristics, such as self-efficacy, habits, and personal innovation also have a certain effect on use behavior. Users' self-efficacy and innovation awareness are the keys to determining whether users can effectively explore the system and use it in depth. In addition, the pleasure motivations of users such as pleasure and enjoyment have a significant influence on use behavior. Many smart devices (such as smart home devices) are designed to create convenience and pleasant experiences for users' life, promoting users to further use the devices.

In addition, the influence of trust in the stage of use is much greater than that in adoption. The reason is that users' adoption of smart services mostly comes from the innovation awareness and impact of the surrounding environment, and users do not have a high level of trust in smart service operators. With the deepening of the understanding of the smart services, the level of trust is getting higher and higher, and the degree of influence on the use behavior is also increasing.

5.3 Continuance

Most research on the continuance of smart city services in the existing literature is based on the theory of information system continuance. Therefore, there are fewer influencing factors, and only perceived usefulness, expectation confirmation and satisfaction are suitable for meta-analysis. All the three factors have significant positive correlations with users' continuance behavior and intention, with satisfaction having the most significant influence.

In addition, unlike perceived privacy risk that can negatively affect users' adoption, privacy concerns have significant relationship with use and continuance. There are two possible reasons for this: 1) During the stages of use and continuance, users' level of concern on the collection and use of their personal information by service operators is not as high as in the stage of adoption; 2) users feel the security of personal privacy information during the use and will not reduce personal intention of use or continuance due to high concern on personal privacy.

5.4 Discussion on the Meta-analysis Result of Moderating Effect

The paper finds that the subject group can also affect the relationship between some factors and the behaviors of smart service users to a certain extent. Social impact, performance expectancy and convenience show a higher impact on the elderly group compared with common users and students, which also confirms the research conclusion of Workman et al. However, subjects of different ages differ greatly in their use experience, habits, and personal cognition. For example, the elderly group is apt to make decisions on whether to use smart services based on the suggestions of others, so the correlation between social influence and user behavior and intention is stronger when the subject is elderly group. Similarly, the student group has relatively rich experience and high information literacy, so factors such as the convenience of service acquisition do not play a decisive role in the use of smart services.

6 Research Conclusion and Limitations

6.1 Research Conclusions

By integrating the research conclusions with large differences, a more comprehensive and universal research conclusion is obtained. In this paper, the research conclusions with different influence natures, influence strengths and effect directions in the existing literature were integrated and quantitatively analyzed with the meta-analysis method; common effect values were used to clarify the relationship between service users' behaviors and intention and the influencing factors, providing a more unified conclusion for the subsequent research in this field. This has certain reference value for smart city service operators in terms of user retention, system development, and advertising, enabling smart city services to be closer to the life of citizens and pay more attention to user experience and requirements, and to some extent also helping with the implementation of smart city services. In addition, smart service operators also need to consider the user groups of their services, and design product service and functions according to the characteristics of the user groups, thus providing targeting smart services and reflecting the human-oriented concept of smart city development from the user level.

6.2 Limitations

In terms of research method, the meta-analysis method requires that k must be greater than 2, so some influencing factors with low frequency of occurrence were not extracted for analysis. In the future, systematic review and meta-ethnography can be combined to conduct a more comprehensive analysis of the factors affecting the behaviors of smart city service users by both qualitative and quantitative analysis. In addition, the paper only examines the moderating effect of the subject group as a moderator on the relationship between some influencing factors and user behaviors. In the future, the moderating effect of moderators such as smart service areas and cultural environments can be tested to explore more moderators, which is also a direction of further research.

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