Research on Factors Influencing Smart Library Users’ Use Intention in the Era of Artificial Intelligence

Jingwen Liu\textsuperscript{1}, Dan Song\textsuperscript{2}\textsuperscript{*} and Weimo Li\textsuperscript{2}

\textsuperscript{1}Library, Huazhong University of Science and Technology, Wuhan 430074, China
\textsuperscript{2}School of Management, Huazhong University of Science and Technology, Wuhan 430074, China
Email: d202081176@hust.edu.cn

Abstract. The arrival of the era of artificial intelligence has promoted the development of smart libraries and endowed them with new features such as autonomy, autonomous learning, context perception, and multi-function. Analyzing how these new features affect users’ behavior is of great significance to the application of artificial intelligence and the optimization of services. Based on the TTF model, the four dimensions of product intelligence (autonomy, adaptability, reactivity, and multifunctionality) are introduced to represent the technology characteristics, and the research model is constructed. And the method of SEM is used to conduct empirical analysis. The results show that technology characteristics and individual characteristics are the main factors affecting the task-technology fit (TTF), while the effect of task characteristics on TTF is not significant. Among them, the impact of technology characteristics is greater than the individual characteristics. The relative importance of the four dimensions of technology characteristics is “Autonomy > Multifunctionality, Reactivity > Adaptability”. The TTF significantly positively affects users’ intention to use smart libraries. Therefore, the suggestions on optimizing smart services are put forward.

Keywords. Artificial intelligence; smart library; influence factors; TTF model.

1. Introduction

Artificial intelligence is the technology imitating human learning and other aspects of intelligence with machines [1]. Experiencing more than 60 years of development, AI has been gradually mature and widely applied in many fields, such as education, health care, finance and so on. It promotes our human society gradually into the era of artificial intelligence.

AI has also brought unprecedented opportunities and challenges to the development of the library field. Gul & Bano [2] define smart libraries as the new generation libraries, which amalgamate smart technologies, smart users and smart services. They believe that smart library is an emerging and innovative technological habitat so that many emerging technologies like internet of things (IoT), data mining and AI will be integrated. Obviously, AI brings new content and features of smart libraries so that it has some impact on users’ use intention. We plan to explore the influencing mechanism of technology characteristics and assess the strength of influence.

Previous studies mainly focus on the practical application of AI in intelligence assistants [3], information recommendation [4], reference and other aspects of library services. But there is the lack of empirical analysis on what changes AI has brought to smart library, and how these changes affect the use. To fill this gap, the research topic of this paper is analyzing the influencing factors of smart library use intention. This study can help us understand how new technologies play an important role in libraries, and how to apply AI technology optimizing services and fit users’ demand.
2. Literature Review

2.1. Smart Library
Driven by IT, the form of library has changed from physical library to digital library. With the rise of IoT and AI technology, smart library will become the new direction of library development. There is no unified definition of the concept of “smart library” at present. Aittola et al. [5] noted that smart library is a mobile library not limited by time and space, which can provide users with perceptual services. And Cao et al. [6] regard smart library as one that can automatically capture the needs of users and provide suitable resources and services to meet those needs. In general, smart libraries can be regarded as the integration of electronic, digital, intelligent, virtual and network libraries, which rely on the technology completely and cannot provide better services without technology [2].

2.2. Technology Characteristics of Smart Library
Smart library is strongly reliant on the technology, including data mining, artificial intelligence, RFID, augmented and virtual technologies, and the Internet of Things (IoT) [2, 6]. The application of these AI technologies makes smart library smarter. This smartness reflected in the following four aspects: First, autonomy. Smart libraries powered by AI perform a certain decision-making autonomy and ability to work independently. For example, Yao et al. [3] present an AI talking robot called Xiaotu, which interact with users in an intelligent manner. Cox et al. [7] hold the opinion that AI can perform tasks like data acquisition and curation, without the intervention of human assistance. Second, autonomous learning (Adaptability). Machine learning enable smart libraries to have strong learning capabilities. Some researchers [8] mention data mining has been used to deliver personalized recommendations service. Combining with machine learning, the intelligent analysis capabilities of content can be enhanced and the effectiveness of services will be improved. Third, context perception (Reactivity). The greatly improved accuracy of face recognition and machine vision has enhanced the context perception ability of smart library, so that it can provide more complex information, even the status information. With the feature of comprehensive perception, AI, IoT and RFID can be integrated with objects (such as books, devices) to track library assets in real-time [9] and to provide contextual information to users [10]. Fourth, multi-function. AI technology supports smart library to realize many functions. Except the functions mentioned above, a smart library with IoT, RFID, sensors, GPS and so forth, can be fully integrated and realized anywhere and anytime, and it can achieve automatic positioning of documents, automatic inventories, unattended security management and self-borrowing, among other services [11].

3. Research Model and Hypothesis

3.1. Research Model
Our research model takes the TTF model as the theoretical basis and integrates autonomy, adaptability, reactivity, and multifunctionality to explore the influencing factors of users’ intention to use smart library. Traditional TTF model is proposed by Goodhue and Thompson [12], which argues that when information technology is used and there is a good matching degree between the technology and the tasks, it can improve the individual performance. In the context of smart library, all terms have developed new meanings and characteristics. To construct a research model with better explanatory power, we introduced the product intelligence proposed by Rijsdijk & Hultink [13] into the model as the technology characteristics. And we chose four dimensions from its components based on specified context analysis. Thus, the specific research constructs and framework are shown in figure 1.

3.2. Research Hypothesis

3.2.1. Task Characteristics. In context of intelligent library, task characteristics reflect the attributes of the activities that meet users’ needs of learning or research. It has been found that task characteristics have a positive effect on TTF in many contexts, such as e-books context [14] and mobile banking context
Based on these findings, we believe the relationship between task characteristics and TTF is also valid in the context of smart library. Therefore, we propose the following hypothesis:

H1: Task characteristics have a positive effect on TTF.

Figure 1. Research model.

3.2.2. Technology Characteristics. In the TTF model, technology characteristics refer to the functional characteristics of information technology that are different from other technologies [12]. Rijndijk & Hultink [13] noted that intelligent products can display a series of capabilities that non-intelligent products do not possess, called product intelligence and measured by seven key dimensions. Smart library is an intelligent product which can collect and process information, supported by AI such as machine learning, knowledge graph and sensors. As the analysis of the smart library scenario shown before, the technical characteristics are reflected in four constructs: autonomy, adaptability, reactivity, and multifunctionality. The studies of Dishaw and Strong [16], Huang, Wu and Chou [17] both proved that technology characteristics have a positive impact on task-technology fit. In this study, with the higher the technology characteristics, there will be stronger ability of AI to provide support and meet user demands, thus improving the TTF degree. As a result, we make the following hypothesis:

H2: Technology characteristics have a positive effect on TTF.

3.2.3. Individual Characteristics. Individual characteristics generally refer to the user's understanding, mastery and use experience of information technology or information system, such as computer literacy [18]. This study takes the variable of self-efficacy as a personal characteristic and adopts to the definition by Bandura [19]. Users who can easily learn to use smart library can gain a more comprehensive understanding of its functions, better utilize different functions to fulfill their own needs, and thus improve their perception of TTF. Therefore, we put forward the bellow hypothesis:

H3: Self-efficacy has a positive effect on TTF.

3.2.4. Task-Technology Fit (TTF). The TTF reflects the degree to which smart library supports the task needs of users. Oliveira et al. [20] found TTF would affect the adoption willingness of mobile banking users. Gan et al. [21] mentioned TTF influences attitude, which in turn affects behavioral intention. In this study, it is clear that the more technology can help individuals accomplish certain tasks, the more willing people are to use it. Accordingly, we hypothesize the following:

H4: TTF has a positive effect on intention to use.

4. Research Method

4.1. Method Design
This study aims to understand users’ intention to use smart libraries and find the influencing factors. To test our theoretical model, we use the questionnaire survey and structural equation model (SEM) method.
The questionnaire consists of two parts: demographic characteristics and the measurement items of each variable. Then, we use SPSS and AMOS as tools to analyze the collected data.

4.2. Data Collection

The respondents of this study are mainly teachers and students in colleges and universities. We distributed the questionnaire through the online platform named questionnaire star and collected a total of 308 questionnaires. Finally, 49 invalid questionnaires (questionnaires with the same answer) were eliminated, and the final number of valid samples was 259, with an effective recovery rate of 84.1%.

4.3. Construct Measurement

In this study, we construct a research model including 9 constructs. In order to ensure the reliability and validity, all constructs are measured using the mature scales from prior IS literatures. We make some modifications of the item expressions to better explain the terms and combine with smart library context. Each item is rated on a Likert 7-point scale, where “1” means “strongly disagree” and “7” means “strongly agree”. All of the variables and items included are listed in table 1.

Table 1. Main variables and items of the questionnaire.

| Variables             | Symbol | Item design                                                                 | Source                                      |
|-----------------------|--------|------------------------------------------------------------------------------|---------------------------------------------|
| Task characteristics  | TAC1   | It perceives information, and proactively provide me with the rich services. | Goodhue & Thompson [12]; Zhou T [15]        |
| TAC 2                 |        | I need to search the resources, layout and use status information of the equipment accurately and efficiently. |                                             |
| TAC 3                 |        | Perceive my position, and automatically plan the optimal reading path or offer intelligently guide to resources. |                                             |
| TAC 4                 |        | Provide precise personalized content recommendation service, based on reading history, interests, and location. |                                             |
| TAC 5                 |        | Provide me with better services, with the passage of time and the accumulation of historical data. |                                             |
| Autonomy              | AU1    | It goes its own way.                                                         |                                             |
| AU2                   |        | It takes the initiative.                                                     |                                             |
| AU3                   |        | It does things by itself.                                                    |                                             |
| Adaptability          | AD1    | It can learn from experience.                                                | Rijndijk & Hultink [13]                     |
| AD2                   |        | It improves itself.                                                          |                                             |
| AD3                   |        | It acts on previous information.                                             |                                             |
| Reactivity            | RE1    | It keeps an eye on its environment.                                          |                                             |
| RE2                   |        | It observes its environment.                                                 |                                             |
| RE3                   |        | It directly adapts its behavior to the environment.                          |                                             |
| Multifunctionality    | MF1    | It can do a lot.                                                             |                                             |
| MF2                   |        | It performs multiple tasks.                                                  |                                             |
| MF3                   |        | It fulfills multiple functional needs.                                       |                                             |
| Self-Efficacy         | SE1    | I could use it if I could call for help when got stuck.                      | Venkatesh et al. [22]                      |
| SE2                   |        | I could learn to use this it if I had a lot of time.                        |                                             |
| SE3                   |        | I could use it if I had the built-in help facility.                         |                                             |
| Task-Technology Fit   | TTF1   | The functions in using library resources are appropriate.                   | Lin & Huang [23]                           |
| TTF2                  |        | The functions in using library resources are enough.                         |                                             |
| TTF3                  |        | In general, the functions of it fully meet my needs.                        |                                             |
| Intention to use      | UI1    | I intend to use It.                                                          | Venkatesh et al. [22]                      |
| UI2                   |        | I predict I would use It.                                                    |                                             |
| UI3                   |        | I plan to use It.                                                            |                                             |
5. Empirical Analysis and Discussion

5.1. Measurement Model Results
Following the two-step approach, we firstly analyzed the measurement model to test the reliability and validity.

5.1.1. Reliability. In this study, internal consistency coefficient (Cronbach’s $\alpha$ coefficient) was measured by SPSS to test the reliability of the questionnaire. As shown in Table 2, all coefficients ranged from 0.715-0.931, greater than 0.7, indicating that the questionnaire passed the reliability test.

Table 2. Reliability and convergence validity test results.

| Variables               | Symbol | Loading | Cronbach’ $\alpha$ | AVE   | CR   |
|-------------------------|--------|---------|--------------------|-------|------|
| Task Characteristics    | TAC1   | 0.730   |                    |       |      |
|                         | TAC 2  | 0.715   |                    |       |      |
|                         | TAC 3  | 0.796   | 0.859              | 0.551 | 0.860|
|                         | TAC 4  | 0.767   |                    |       |      |
|                         | TAC 5  | 0.698   |                    |       |      |
|                         | AU1    | 0.704   |                    |       |      |
| Autonomy                | AU2    | 0.863   | 0.715              | 0.503 | 0.745|
|                         | AU3    | 0.520   |                    |       |      |
|                         | AD1    | 0.878   |                    |       |      |
| Adaptability            | AD2    | 0.879   | 0.887              | 0.730 | 0.890|
|                         | AD3    | 0.804   |                    |       |      |
|                         | RE1    | 0.852   |                    |       |      |
| Reactivity              | RE2    | 0.932   | 0.919              | 0.796 | 0.921|
|                         | RE3    | 0.89    |                    |       |      |
|                         | MF1    | 0.872   |                    |       |      |
| Multifunctionality      | MF2    | 0.925   | 0.929              | 0.821 | 0.932|
|                         | MF3    | 0.92    |                    |       |      |
|                         | SE1    | 0.674   |                    |       |      |
| Self-Efficacy           | SE2    | 0.786   | 0.815              | 0.607 | 0.821|
|                         | SE3    | 0.866   |                    |       |      |
|                         | TTF1   | 0.838   |                    |       |      |
| Task-Technology Fit     | TTF2   | 0.875   | 0.871              | 0.699 | 0.875|
|                         | TTF3   | 0.794   |                    |       |      |
|                         | UI1    | 0.814   |                    |       |      |
| Intention to Use        | UI2    | 0.854   | 0.865              | 0.685 | 0.867|
|                         | UI3    | 0.814   |                    |       |      |
|                         | AU     | 0.813   |                    |       |      |
| Technology characteristics | AD    | 0.685   | 0.789              | 0.598 | 0.856|
|                         | RE     | 0.789   |                    |       |      |
|                         | MF     | 0.795   |                    |       |      |

5.1.2. Validity. We conducted a CFA to examine the validity, which consists of convergent validity and discriminate validity. As shown in table 2, composite reliabilities (CRs) of constructs ranged from 0.745-0.923, average variance extracted (AVE) ranged from 0.503-0.821, and the standard factor loadings ranged from 0.520-0.925. All constructs met the acceptable standard (CRs$>0.7$, AVE$>0.5$, and factor loading$>0.5$). This suggested that a high convergent validity of the data existed.

The discriminant validity reflects whether the correlation between different factors is as small as possible. The square root of AVE of each variable was significantly greater than its correlation coefficient with other factors (table 3), demonstrating the scales had good discriminate validity.
Table 3. Correlation coefficient between latent variables and square root of AVE.

|     | TAC  | AU   | AD   | RE   | MF   | SE   | TTF  | UI   |
|-----|------|------|------|------|------|------|------|------|
| TAC | 0.742|      |      |      |      |      |      |      |
| AU  | .219 | 0.709|      |      |      |      |      |      |
| AD  | .194 | .519 | 0.854|      |      |      |      |      |
| RE  | .258 | .587 | .543 | 0.892|      |      |      |      |
| MF  | .352 | .504 | .489 | .555 | 0.906|      |      |      |
| SE  | .365 | .371 | .433 | .447 | .513 | 0.779|      |      |
| TTF | .276 | .425 | .326 | .479 | .564 | .505 | 0.836|      |
| UI  | .392 | .357 | .371 | .448 | .544 | .579 | .442 | 0.828|

Note: **p< 0.01; The value on the diagonal in the matrix is the square root of AVE.

5.1.3. Second-Order CFA. Our model contains the technology characteristics as a second-order factor, which is composed of four first-order factors, namely autonomy, adaptability, reactivity, and multifunctionality. The correlation coefficients among the four first-order variables were generally greater than 0.5, or close to the standard, indicating that the second-order CFA can be carried out. The model fit indices of second-order CFA can be obtained in table 4. The target coefficient value in this study was 0.931, which was relatively ideal, revealing the scale in this study was suitable to be made a second-order model. As shown in table 2, the factor loading of each item was all greater than 0.685, which was in line with the criterion of >0.5, AVE value was 0.598 >0.5, and CR value was 0.856 >0.7, which indicated that the second-order model had good convergent validity.

Table 4. Model fit index summary.

|                | $\chi^2$ | df  | $\chi^2$/df | RMSEA | CFI  | IFI  | TLI  | NFI  |
|----------------|----------|-----|-------------|-------|------|------|------|------|
| Standard       |          |     |             |       |      |      |      |      |
| First-order CFA| 468.8    | 271 | 1.730       | 0.053 | 0.955| 0.955| 0.946| 0.9   |
| Second-order CFA| 503.6    | 285 | 1.767       | 0.055 | 0.95 | 0.95 | 0.943| 0.893 |
| Structural Model| 576.0    | 288 | 2.000       | 0.062 | 0.934| 0.935| 0.926| 0.877 |

Note: The target coefficient= first-order diagonal $\chi^2$/ second-order $\chi^2$

5.2. Structural Model Results

To test the significance and magnitude of each hypothesized path and the explanatory power of the overall model, we used Amos to conduct SEM and report the results in figure 2.

![Figure 2. Hypothesis test results.](image)

Three paths were significant with a t-value of at least 2.58, while one path with a t-value less than 1.96 was not significant. We found that all but one of the hypotheses were supported. As expected, technology characteristics and individual characteristics were positively related to TTF ($\beta$=0.504,
p<0.01; β=0.305, p<0.01), supporting H2, H3. TTF had a positive effect on intention to use (β=0.580, p<0.01), supporting H4. However, against hypothesis, task characteristics had no impact on TTF (β=0.016, t=0.063); thus, H1 was not supported. The model explained 56 percent (R²=0.56) of variance in TTF; 34 percent (R²=0.34) of the variance in the intention to use the smart library, which meant that the model had a moderate explanatory power.

Some fit indices of model were listed in table 4. The results showed that the fit indices were all within or close to the threshold of the recommend values [24].

5.3. Discussion
Based on the results of the above analysis, the following four important viewpoints are proposed:

First, both technology characteristics and individual characteristics positively affect TTF. The higher level of technology characteristics means they can better satisfy the different task needs, so that users can timely and accurately perform tasks, leading to higher TTF. For individual characteristics, when users are confident in their self, they can use new technologies in an easier starting and deeper exploring way, thus obtaining higher perceptual matching (i.e., TTF) and better experience. It's worth noting that technology characteristics has a more significant effect on TTF than self-efficacy. In other words, promoting TTF by improving technology characteristics is a more effective path.

Second, TTF affect intention to use positively. If the TTF is high, it means that smart library can provide users with rich and proper functions, fulfill users’ needs, therefore, users are more willing to use smart library. We argue that it is useful to understand users’ use intention in perspective of TTF. It basically explains how technology characteristics work and considers with user-centric approach.

Third, the effect of task characteristics on TTF is not significant. This conclusion is inconsistent with the existing research [14, 15]. The cause of this phenomenon may be the fact that the current users’ task needs have developed with new content in smart library scene, some of which are already being satisfied by AI technology, and some of which still need to be improved, thus canceling each other out. In the future, we may explore task characteristics further.

Finally, the order of relative importance of the four dimensions of technology characteristics is: Autonomy> Multifunctionality, Reactivity> Adaptability. The factor loading of these four dimensions on the second-order variables are 0.813, 0.685, 0.789 and 0.795, respectively. The larger the factor loading is, the closer the relationship between the first-order variable and the second-order variable is. Accordingly, we get the relative importance ranking, which can help us know how to better improving technology characteristics and which dimension is the top priority when resource is restrained.

6. Conclusion
On the basis of the TTF model, this study constructs a model of influencing factors of the smart library users’ use, and empirical tests the model by survey and SEM. The results show that both technology characteristics and individual characteristics have a significant positive effect on TTF, then influencing intention to use smart library. The effect of technology characteristics on TTF is stronger compared to individual characteristics. And task characteristics is not significant effective on TTF.

Therefore, we put forward two suggestions as follows: One is that different AI technologies have different advantages, and the fit should be considered when introducing new technologies into services. The other is, it is very necessary to provide relevant tips and help functions for smart library users, especially to provide a variety of alternative help methods.

Of course, there are some limitations in this study, such as small sample size, which may bring some deviations to the research results. It can be considered in the future to comprehensively consider other factors and further separate the influences that the specific task characteristics may cause.

Acknowledgments
This research is funded by the Research Fund Program of Hubei Academic Library Committee (Program number: 2019-ZD-01).
References

[1] Muggleton S 2014 Alan Turing and the development of artificial intelligence *AI Communications* **27** 3-10.

[2] Gul S and Bano S 2019 Smart libraries: An emerging and innovative technological habitat of 21st century *Electron. Libr.* **37** 764-83.

[3] Yao F, Zhang C and Chen W 2015 Smart talking robot Xiaotu: Participatory library service based on artificial intelligence *Libr. Hi Tech* **33** 245-60.

[4] Hahn J 2011 Location-based recommendation services in library book stacks *Ref. Serv. Rev.* **39** 654-74.

[5] Aittola M, Ryhänen T and Ojala T 2003 SmartLibrary—Location-Aware Mobile Library Service *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* pp 411-6.

[6] Cao G, Liang M and Li X 2018 How to make the library smart? The conceptualization of the smart library *Electron. Libr.* **36** 811-25.

[7] Cox A M, Pinfield S and Rutter S 2019 The intelligent library *Libr. Hi Tech* **37** 418-35.

[8] Simović A 2018 A Big Data smart library recommender system for an educational institution *Libr. Hi Tech* **36** 498-523.

[9] Dishaw M T and Strong D M 1998 Supporting software maintenance with software engineering tools: A Computed task-technology fit analysis *J. Syst. Softw.* **44** 107-20.

[10] Gefen D, Straub D and Boudreau M-C 2000 Structural equation modeling and regression: guidelines for research practice *Commun. Assoc. Inf. Syst.* **4**.