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# The Quantitative Research on Behavioral Intention towards 5G Rich Communication Services among University Students

**Zhiyuan Yu [1,*], Jianming Wu [1], Xiaoxiao Song [1], Wenzhao Fu [1] and Chao Zhai [2]**

1 School of Journalism and Communication, Shandong University, Jinan 250100, China
2 School of Information Science and Engineering, Shandong University, Qingdao 266237, China
* Correspondence: yuzhiyuan@sdu.edu.cn

**Abstract:** Supported by artificial intelligence and 5G techniques in mobile information systems, the rich communication services (RCS) are emerging as new media outlets and conversational agents for both institutional and individual users in China, which inherit the advantages of the short messaging service (SMS) with larger coverage and higher reach rate. The benefits can be fulfilled through media interactions between business and smart phone users. As a competitor of over-the-top services and social media apps, the adoption of RCS will play a vital role for mobile users. It is important to conduct quantitative research and reveal the behavioral intention to use (BIU) among RCS users. In this paper, we collect 195 valid respondents from university via an offline experiment and then build a structural equation model consisting of task characteristics (TAC), technology characteristics (TEC), task-technology fit (TTF), performance expectancy (PE), perceived risk (PR), perceived trust (PT), perceived convenience (PC) and satisfaction (SA). We find that SA, PC and PE have direct impact on BIU. TTF has indirect path connecting to BIU via PE and SA. The impacts of PT and PR on BIU are not significant. Performance results show that our proposed model could explain 49.2% and 63.1% of variance for SA and BIU, respectively. Through revealing the influencing factors of BIU, we can point out the user perception of the brand-new interactive channel and then provide the guidance for the large-scale commercialization of 5G RCS.

**Keywords:** 5G; rich communication services; media interaction; task-technology fit; behavioral intention; university students

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## 1. Introduction

Relying on the advantages of lower cost and higher reach rate, the short message service (SMS) has been widely used by individuals and organizations to keep in touch with target users directly. For example, 80% of people use SMS for business communications thanks to the merits of it being fast and unobtrusive [1]. The open and click-through rates of text messages are 98% and 19%, respectively [2]. From the statistical report, we can see that SMS is still an active outlet with sufficient total messaging numbers in German, US and China. In Germany, nearly 7 billion text messages were sent in 2020 [3]. Mobile users in the US exchanged more than 119 billion messages and sent a total of 2.2 trillion SMS and multimedia messaging service (MMS) [4]. In China, the volume of mobile SMS has gradually climbed to 1761.95 billion in 2021 [5].

Based on GSMA Universal Profile 2.0+ standards, rich communication services (RCS) can be viewed as updated SMS with person to person (P2P) and application to person (A2P) interaction modes, which is as killer application of 5G mobile system. Supported by message as a platform (MaaP) and sophisticated techniques (e.g., AI, big data and cloud computing) in mobile information systems, RCS contain the functions of plain text, voice assistant, graphics, chatbot, stream media, extended reality, status bar, shopping, payment, and location-based services, etc., from the native SMS portal in 5G-enabled mobile phones. Mobile users no longer need to download or install external applications, but they can enjoy one-step services with app-like experiences, which facilitate the human–machine interaction on smartphones. Moreover, supported by intelligent text and natural language processing, users can not only use multiple formats of messaging, but also interact with service providers through chatbots. The human–computer interaction is further facilitated by 24-h instant responses. The efficiency of two-way conversation and the response rate of enterprises can be guaranteed.

As an emerging converged communication application, RCS integrate content and service vendors (e.g., tele-operator, organization or company) and offer differentiated contents for both industry and individual users. New ecosystems can be formed to further reduce the complexity of human–computer interaction. The connection among government, enterprises and users will be enhanced by strong reminders and attractive contents. Compared with the traditional media and over-the-top (OTT) channels, RCS provide another choice and promote the construction of omni-media environment.

*Research Question*

Nowadays, RCS have been deployed widely in Europe (e.g., Vodafone for United Kingdom, Orange for France, Deutsche Telekom for Germany), North America (Verizon Wireless for USA, Rogers for Canada), Asia Pacific regions (SK Telecom for Korea, NTT and KDDI for Japan) by the operators. Until January 2022, there have been 421 million global monthly active users and 1.2 billion ready devices [6]. Juniper Research forecasts that the number of RCS-capable users will increase from 1.2 billion in 2022 to 3.8 billion in 2026 and the revenue varies from 230 million dollars to more than 4.6 billion dollars [7]. As a vital and direct channel, business companies can benefit from A2P mode to engage with their target customers. For example, the number of Japaneses RCS users grows rapidly after launching with more than 85% open rate for rich business messaging, which shows a higher level of engagement [8].

Since April 2020, Chinese operators (i.e., China Mobile, Telecom and Unicom) have released the 5G RCS white paper and announced to start the pre-commercial trial. A serials of A2P Demos and use cases are successively proposed for all works of life; however, due to the limitations of 5G RCS-enabled devices and the interoperability, until the November 2021 and January 2022, China Unicom and Telecom have just launched the commercialization of 5G RCS for corporate customers and individuals, respectively. Although mobile users are quite familiar with SMS and other mature OTT applications, 5G-enabled RCS are still fresh converged communication product. For operators, original equipment manufacturer, aggregators and platform providers, users' perceptions and reactions about 5G-enabled RCS can help to ameliorate service experiences and adapt to local circumstances.

In this study, we recruited university students to participant in an offline experiment, because 27.8% and 41% of 5G-capable phone owners are under 24 and 25–34 years old in 2021 [9]. Those two groups have rich experiences in using OTT and social media applications. University students (including undergraduate and graduate) are within those two groups and were chosen as participants in our experiment. As a timely application, user satisfaction and usage intention are two important metrics to evaluate the technology acceptance. Many researchers have studied the influencing factors of behavioral intention to use (BIU) in the field of mobile learning [10–12], mobile banking [13,14], blockchain [15], biometric identification [16] and open data technologies [17]. User satisfaction can significantly influence individuals' BIU for particular systems [18]. As an upgraded application, few researchers have ever studied the BIU of 5G RCS; therefore, it is urgent to study the satisfaction and behavioral intention towards RCS before the large-scale commercial usage. The research questions (RQ) are proposed as follows:

- RQ1: What are the factors that influence users' intentions to use 5G RCS among university students?
- RQ2: How do influencing factors affect users' intentions to use 5G RCS among university students?

The rest of this paper is organized as follows: Section 2 presents the literature review about unified theory of acceptance and use of technology (UTAUT), TTF and usage of SMS. Section 3 explains the proposed theoretical model and describes the hypotheses among constructs. Sections 4 and 5 present the research methods and data analysis result. Section 6 discusses the main findings and summarizes insights. Finally, Section 7 concludes this paper.

## 2. Literature Review

### 2.1. The Usage of SMS

Currently, SMS still plays important roles in various fields, e.g., emergency warning, agricultural production, government affairs, public welfare and medical health care. SMS can assist people with health management and intervention. Islam et al. found that people are willing to receive and pay for SMS of Health Information in Bangladesh [19]. SMS can promote family planning education, consultation and interaction [20]. During the COVID-19 pandemic, SMS can serve as an early warning system to track infected COVID-19 patients effectively, and help to transfer patients with worsening conditions to hospital care [21]. Yu et al. revealed that the respondents showed positive attitudes toward public-interest SMS [22]. As an efficient and economical flow control method, SMS can reduce unnecessary outpatient visits, thus striving for valuable time for medical staff to control COVID-19 [23]. Moreover, SMS can be adopted as an important public health tool for spreading mental health management strategies, which can effectively reduce the psychological burden of COVID-19 pandemic [24]. In addition, SMS also brings effective intervention to postoperative pain management [25], smoking cessation [26] and vaccination [27].

Furthermore, SMS has won the favor of government agencies with the advantage of high reading rate. Government agencies can timely release epidemic information and policy announcements to the public, which can effectively reduce the social instability. Katona et al. found that the monitoring system based on low-cost SMS can supplement and eventually replaced the traditional paper system to predict medical emergencies faster, so as to improve the public health situation in Vietnam [28]. Shareef et al. found the critical factors of time, relevance and reliability affected people's attitude towards SMS for public service management [29].

### 2.2. Theoretical Background

In order to investigate users' preference over emerging techniques, some technology acceptance models have been proposed to reveal the influencing factors towards the attitudes and usage intention. UTAUT and task-technology fit (TTF) are popularly used to explain the reason of usage behavior.

UTAUT model is generated from the study of intentions to use information system (IS). Based on technology acceptance model and theory of planned behavior, Venkatesh et al. showed that performance expectation (PE), effort expectation (EE) and social influence (SI) significantly affect behavioral intention (BI). Meanwhile, the facilitating conditions (FC) significantly affects users' behavior [30]. Depending on the explanatory ability, researchers always adopt this model in the fields of mobile payment [31,32], mobile healthcare [33,34]. Beza et al. showed that the intentions to adopt mobile SMS for agricultural data provision can be predicted by PE, EE and other constructs [35]. Alwahaishi et al. revealed that PE, SI and FC significantly affected BI regarding to the usage of information and communications technology (ICT) [36]. In government organizations, Guptaa et al. revealed that PE, EE, SI and FC all positively affected the usage of ICT to enhance interactions with employees [37]. Narine et al. indicated that PE, EE and SI are the positive factors of the farmers' intentions to use SMS [38]. In terms of Chatbot usage studies, Melián González et al. revealed that the intentions of chatbots usage for travel are directly influenced by PE and SI [39].

Task-technology fit (TTF) model consists of task characteristic and technology characteristic, which aims to better understand the linkage between IS and individual performance.

This model is addressed to the concerns that existing models fail to properly explain how IS affects individual performance [40]; however, by considering the fit between task and technology characteristics, TTF model has been widely used to investigate the correlation between task, technology, utilization, users'satisfaction and performance, especially to explain users' performance when using the mobile technology, such as location-based systems [41], online shopping [42,43], wearable technology [44] and so on.

In term of technology acceptance of SMS, Bergvik et al. found that Internet use, gender and open personality traits have a positive predictive effect on SMS usage [45]. Park et al. showed that the number of text messages sent and received were related to reduce loneliness through higher levels of intimacy and relationship satisfaction [46]. Furthermore, Lai pointed that a positive correlation was existed between satisfaction and intention to continuously use SMS among customers [47]. Pruthikrai et al. found that participants who confident in their ability had positive attitude on the usage of SMS [48]. Similarly, Cho et al. showed that the attitude of SMS is positively affected by its perceived communication effectiveness, perceived ease of use and subjective norms [49]. In addition, Turel et al. found that perceived value will positively affect people's BIU of SMS and then promote the actual usage [50]. Kim et al. pointed that the antecedents of the intention to continue using SMS services include perceived usefulness, perceived ease of use, perceived monetary value and perceived enjoyment [51]. Lu et al. also revealed that perceived usefulness has a positive impact on BIU of SMS [52]. The main findings of related works in the fields of SMS and Chatbot are presented in Table 1.

**Table 1.** Main results of prior study.

| **Chatbot Usage** | | **SMS Usage** | |
|---|---|---|---|
| **Main Research Findings** | **Source** | **Main Research Findings** | **Source** |
| Information quality → Satisfaction<br>Service quality → Satisfaction<br>Perceived enjoyment → Satisfaction<br>Perceived usefulness→ Satisfaction<br>Perceived enjoyment → Continuance intention<br>Perceived usefulness → Continuance intention | Ashfaq et al. [53] (2020) | Performance expectancy → Behavioral intention<br>Effort expectancy → Behavioral intention<br>Price value → Behavioral intention<br>Trust → Behavioral intention | Beza et al. [35] (2018) |
| Perceived usefulness → Adoption intention<br>Perceived ease of use → Adoption intention<br>Perceived trust →Adoption intention<br>Perceived intelligence →Adoption intention<br>Anthropomorphism → Adoption intention<br>Adoption intention → Actual use | Pillai et al. [54] (2020) | Overall perceived value → Intentions<br>Perceived quality → Overall perceived value<br>Perceived emotional value → Overall perceived value<br>Perceived value-for-money → Overall perceived value<br>Perceived social value → Overall perceived value<br>Intentions → Usage | Turel et al. [50] (2007) |
| Performance expectancy → Usage intention<br>Social influence → Usage intention<br>Hedonic motivations → Usage intention<br>Habit → Usage intention<br>Attitude → Usage intention<br>Inconveniences → Usage intention<br>Anthropomorphism → Usage intention<br>Automation → Usage intention | Melián González et al. [39] (2021) | Perceived enjoyment → SMS adoption<br>Perceived monetary value → SMS adoption<br>Perceived usefulness → SMS adoption<br>Perceived ease of use → SMS adoption | Kim et al. [51] (2008) |
| Perceived usefulness → Intention to Adopt<br>Perceived usefulness → Attitude<br>Perceived ease of use → Intention to Adopt<br>Perceived ease of use → Attitude<br>Attitude → Intention to Adopt<br>Perceived convenience→ Intention to Adopt<br>Perceived convenience →Attitude<br>Perceived convenience → Perceived usefulness<br>Perceived convenience →Perceived ease of use<br>Intention to Adopt → Enhanced Performance | Malik et al. [55] (2021) | Perceived enjoyment → Actual usage<br>Perceived network externalities → Actual usage<br>Perceived usefulness → Actual usage<br>Communication effectiveness → Actual usage<br>Perceived service cost → Actual usage | Lu et al. [52] (2010) |

The contribution of this paper can be summarized as follows:

- According to the literature review, we find that few researchers have ever studied the behavioral intention to use 5G RCS among mobile users in China and other countries, although the RCS have already been deployed and realized commercial use in some areas. As a convenient interactive outlet with business and individual users, we conduct a quantitative research to reveal the intentions to use 5G RCS among university students through offline experiment.

- Based on UTAUT and TTF theory, we propose a structural equation model with the influencing factors of task characteristics, technology characteristics, task-technology fit, performance expectancy, perceived risk, perceived trust, perceived convenience and satisfaction for the 5G RCS usage intentions.
- We find that the proposed model has relatively better explanation for the behavioral intention to use 5G RCS among the recruited participants. Therein, satisfaction, perceived convenience and performance expectancy directly affect BIU. Although TTF has no direct significant path connecting to BIU, the indirect paths via TTF→PE→SA→BIU and TTF→PE→BIU exist, which reveals that BIU is largely determined by satisfaction only when the technique benefit and service quality meet the requirements of mobile users.

## 3. Theoretical Model and Hypotheses

Based on UTAUT and TTF models, we design a structural equation model (SEM) by integrating the constructs of task characteristics (TAC), technology characteristics (TEC), task-technology fit (TTF), performance expectancy (PE), perceived risk (PR), perceived trust (PT), perceived convenience (PC), based on which we investigate the users' satisfaction (SA) and behavioral intention to use (BIU) regarding to RCS among mobile users. The definition of each construct is shown in Table 2.

**Table 2.** Construct definition.

| Construct | Definition | Reference |
|---|---|---|
| TAC | The characteristics that 5G RCS might be more necessary for mobile users' needs. | [56] |
| TEC | The characteristics perceived by users when 5G RCS offering services actively or passively. | [56] |
| TTF | The degree to which 5G RCS assist mobile users in performing the portfolio of tasks. | [56] |
| PE | The benefits that individuals believe will be brought to them by using 5G RCS. | [30] |
| PC | The convenience of using 5G RCS or brought by 5G RCS. | [57] |
| PT | The degree to which individuals can use 5G RCSto guarantee service completion and the trust of the content. | [58] |
| PR | The degree of risks that individuals feel when using 5G RCS. | [59] |
| SA | The degree of personal interest in 5G RCS which provides. | [60] |
| BIU | The individual's willingness to use 5G RCS. | [30] |

We present our proposed theoretical model in Figure 1 and then describe the relative relationships among the constructs as follows.

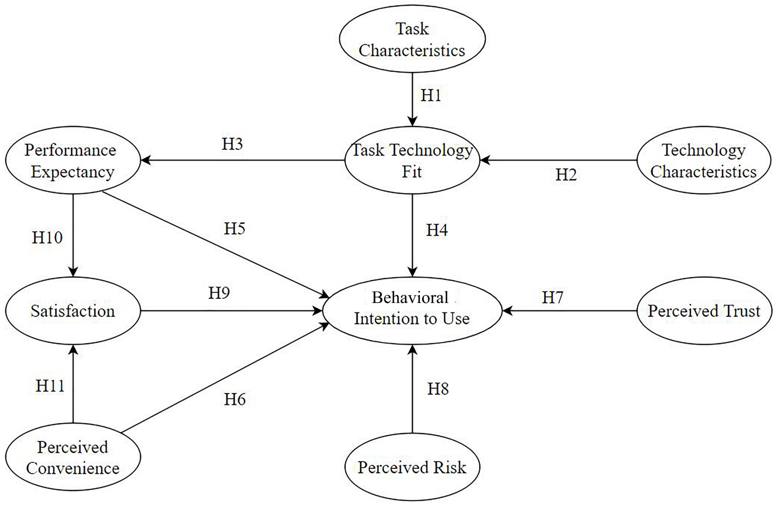


**Figure 1.** The proposed theoretical model.

### *3.1. Task-Technology Fit*

TTF focuses on to what extent the characteristics and capabilities of a technique match the demands of a specific task [61], which is viewed as the vital factor to explain the BIU of new technology [62,63] . Goodhue et al. showed that technology characteristics and task characteristics positively affect TTF, which further influence the usage of IS and the individual performance [56]. Zhou et al. found that the TEC and TAC have a positive impacts on TTF in mobile banking, and meanwhile TTF has a positive influence on PE and user acceptance [64]. Similarly, Oliveira et al. verified the same result between TEC, TAC and TTF for the adoption of mobile banking in Portugal [65]. Shahbaz et al. revealed that TTF affected PE and BIU towards the usage of air pollution management system positively [66]. Sahid et al. found that TTF is one of the factors to positively influence BIU of big data analysis in Malaysian government [67]. In this paper, we hypothesize:

**Hypothesis 1 (H1).** *TAC of 5G RCS affect the TTF positively.*

**Hypothesis 2 (H2).** *TEC of 5G RCS affect the TTF positively.*

**Hypothesis 3 (H3).** *TTF of 5G RCS has a positive impact on PE.*

**Hypothesis 4 (H4).** *TTF of 5G RCS has a positive impact on BIU.*

### *3.2. Performance Expectancy*

One of the most important factors in UTAUT is PE, which describes the degree to which the individuals think that the usage of IS help them achieve gains for the performance [30]. Shen et al. found PE has a positive and significant effect on students' BIU of wearable head-mounted displays (HMDs) in learning [68]. Andrews et al. pointed out that PE has a positive influence on librarians' intention to adopt AI-related technologies [69]. Moreover, PE influences the intention of continuance behavior of Video-conference platforms positively [70]. For the mobile registration apps, PE has a positive impact on the intention to use among the elder group [71]. Hence, we hypothesize:

**Hypothesis 5 (H5).** *PE has a positive impact on BIU of 5G RCS.*

### *3.3. Perceived Convenience*

PC is a significant factor that can affect individuals' adoption of new technologies. Huang et al. found that using a chatbot for veterinary consultation is convenient [72]. Hossain et al. investigated the factors that affect consumer acceptance of RFID technology and found that higher PC of RFID technology lead to greater acceptance of this technology [57]. Malik et al. revealed that PC positively impacts student's attitude towards chatbots adoption and students' intention to adopt chatbots [55]. Hence, we hypothesize:

**Hypothesis 6 (H6).** *PC has a positive impact on BIU of 5G RCS.*

### 3.4. Perceived Trust

Trust is the foundation of consumption, purchase and usage, which is defined as a psychological condition that includes accepting vulnerability based on positive expectations of others' intentions or behaviors [58]. Gefen specified the variable of trust in e-commerce and believed that trust is the willingness to depend for e-commerce [73]. Pillai et al. found that PT significantly positively affected the adoption intention of AI powered Chatbots for travel planning, where trust relates to the traveler's perception of privacy protection, security and quality of information and services provided [54]. When exploring the influencing factors of mobile payment, Al-Saedi et al. added PC and PR on the basis of UTAUT model and found PT can positively affect the BIU of mobile payment, while PR has no significant impact [74]. There existed a positive effect of PT on intention to use when studying online information services [75]; therefore, we assume that:

**Hypothesis 7 (H7).** *PT has a positive impact on BIU of 5G RCS.*

### 3.5. Perceived Risk

Perceived risk is powerful at explaining consumers' behaviors [76], which is the main obstacle for users to accept new technologies [77,78]. It is defined as the potential for loss in the pursuit of a desired outcome of using electronic service, which had a negative impact on individuals' intention to use [59]. For the adoption of Internet banking, Martin et al. found that PR did have a negative impact on the intention to use [79]. Similarly, Xie et al. revealed that PR plays an extremely negative effect on intention of FinTech platforms [78]. In India, Thakur also found that PR is a significant negative factor on adoption usage intention of mobile payment services [80]. Lawson-Body et al. revealed that PR has a significant negative impact on acceptance of e-books among students [81]. So, we propose:

**Hypothesis 8 (H8).** *PR has a negative impact on BIU of 5G RCS.*

### 3.6. Satisfaction and Behavioral Intention to Use

Satisfaction and BIU are important dependent variables to understand the acceptance of a new technology or application, which helps to continuously meet the requirements of the users. Satisfaction represents an accumulated feeling developed with multiple interactions [82]. BIU is defined as a measure of the strength of one's intention to perform a specified behavior [83]. According to the use and gratification theory, satisfaction is obtained by individuals during the process of using specific media.

Alowayr found that perceived satisfaction is a positive and significant factor of intention to use mobile learning [84]. Ashfaq et al. revealed that satisfaction is a strong determinant and predictor of users' continuance intention toward chatbots e-service [53]. Chao indicated that satisfaction has a positive impact on college students' BIU of mobile learning and PE has a positive impact on satisfaction [18]. Malik et al. revealed that PC positively affected students' attitude towards the adoption of chatbots [55]. Hence, we hypothesize:

**Hypothesis 9 (H9).** *SA has a positive impact on BIU of 5G RCS.*

**Hypothesis 10 (H10).** *PE has a positive impact on SA of 5G RCS.*

**Hypothesis 11 (H11).** *PC has a positive impact on SA of 5G RCS.*

## 4. Research Method

### 4.1. Data Collection

Considering the less universality of RCS-capable smartphones and the campus COVID-19 prevention measures, we recruited undergraduate and graduate students from Central Campus in Shandong University and then conducted offline experiments using the prepared 5G-RCS-enabled mobile phones from 8 April 2022 to 30 May 2022, which strictly follows COVID-19 quarantine rules (e.g., keeping social distance, wearing mask and disinfecting). Each participant was well informed on the purpose of the research and the data use policy to ensure anonymity before the offline experiment. In total, 199 students participated in the offline experiment. Therein, 195 of 199 questionnaires were valid, which was greater than 10 times the largest number of paths [85]. The informed consent was also obtained from all participants.

The offline experiment consists of three steps: (1) Playing a short video introduction about 5G RCS; (2) operating and interacting with the RCS accounts according to the guideline shown in Appendix Table A2, which cover all kinds of service types and with complete functions; (3) after finishing above the steps, each participant fills a questionnaire based on the experience. Each item shown in Appendix Table A1 was scaled by seven-point Likert scale ranging from "1 (Strongly Disagree)" to "7 (Strongly Agree)". No missing values for the valid data after checking. The average duration is about 30 min for each participant.

### 4.2. Demographic Characteristics

We used the screened data for demographic analysis and the characteristics are shown in Table 3 and 4. The proportion of male and female participating in the survey was about 3:7. For the education level, the proportional between undergraduate and graduate was 56.92% and 43.08%. The age of respondents ranged from 18 to 29 years old and the median age was 22.

**Table 3.** The demographic characteristics (N = 195).

| Characteristic | Category | Frequency | Percentage |
|---|---|---|---|
| Gender | Male | 49 | 25.13 |
| | Female | 146 | 74.87 |
| Education | Undergraduate | 111 | 56.92 |
| | Graduate | 84 | 43.08 |
| Major | Humanities and Social Sciences | 151 | 77.44 |
| | Science | 44 | 22.56 |
| Reading SMS frequency | 3 times a month or less | 37 | 18.97 |
| | 4 to 10 times a month | 80 | 41.03 |
| | 11 to 19 times a month | 41 | 21.03 |
| | 20 times a month or more | 37 | 18.97 |
| Sending SMS frequency | No sending | 99 | 50.77 |
| | 1–5 per month | 90 | 46.15 |
| | 6–10 per month | 6 | 3.08 |

**Table 4.** (Continued.) The demographic characteristics (N = 195).

| Characteristic | Num. | Min. | Max. | Mean | Median | SD |
|---|---|---|---|---|---|---|
| Age (one full year of life) | 195 | 18 | 29 | 21.61 | 22 | 2.420 |
| Monthly rent (CNY) | 195 | 8 | 300 | 45.42 | 38 | 34.766 |

From the characteristics of SMS usage behaviors, more than 80% of participants read text messaging more than four times a month, of which 4 to 10 times account for 41.03%. 18.97% of the respondents read at least 20 times per month. It means that those participants have the habits of SMS usage and would like to read the received messages to a certain degree; however, in terms of sending behavior among the last three months, the percentage of no sending participants accounts for 50.77%. It basically reveals the dilemma of SMS. In addition, 46.15% of respondents sent one to five text messaging and only 3.08% of that sent 6 to 10 messages per month. We can see that respondents prefer to read short messages rather than sending. From Table 4, the participants' telephone monthly rent fee ranges from 8 CNY to 300 CNY with a large two-level differentiation. The average spent money on telephone bill is about 45.42 CNY.

## 5. Data Analysis

### *5.1. Measurement Model*

We use structural equation model analysis software, Smart PLS 3, to validate the hypothetical model. As a variance-based method, PLS-SEM estimates path coefficients to maximize the $R^2$ values of the endogenous constructs [85]. Compared with other methods (e.g., LISREL, AMOS), partial least squares structural equation model (PLS-SEM) requires relatively small sample sizes and performs well in prediction [86], which is suitable for exploratory studies and fit with our study.

According to the Hulland criterion, the factor loading for each problem item is recommended to be larger than 0.5 and preferably greater than 0.7 when performing the PLS-SEM analysis [87]. Cronbach $\alpha$ and composite reliability (CR) are both used to assess the consistency reliability of each construct, which should be at least 0.6 [88] and well above 0.7 [89]. The average variance extracted value (AVE) aims to test the convergent validity, with a minimum value greater than 0.5 [90,91], indicating that the construct explains more than 50% of the variance of its indicators on average. In addition, the discriminant validity is determined by the Fornell–Larker criterion test. The square root of the AVE value should be higher than the latent variable correlation [91]. The specific analysis results are presented as follows.

As can be seen in Table 5, the square root of each construct's AVE is greater than its highest correlation with other constructs. As shown in Table 6, the factor loading of each item among all constructs are greater than 0.6, varying between 0.644 to 0.926. Except for TAC3, TEC4, PC5, PR2 and PR3, the remaining items are greater than 0.7. Overall, each construct has good factor loading and the indicator reliability meets the requirements. The Cronbach's $\alpha$ coefficients of all the constructs were greater than 0.7 except for the construct TAC, which was between 0.6 and 0.7. The composite reliability of all the constructs is greater than 0.7. The AVE values of each construct were higher than 0.5; therefore, in general, the reliability and validity of the scale are relatively satisfactory and reflect the accuracy of this study to some extent.

**Table 5.** Discriminant validity (Fornell–Larcker criterion).

| | BIU | PC | PE | PR | PT | SA | TAC | TEC | TTF |
|---|---|---|---|---|---|---|---|---|---|
| **BIU** | **0.893** | | | | | | | | |
| **PC** | 0.640 | **0.764** | | | | | | | |
| **PE** | 0.598 | 0.712 | **0.802** | | | | | | |
| **PR** | −0.249 | −0.098 | −0.115 | **0.721** | | | | | |
| **PT** | 0.429 | 0.456 | 0.469 | −0.173 | **0.840** | | | | |
| **SA** | 0.779 | 0.678 | 0.620 | −0.271 | 0.535 | **0.855** | | | |
| **TAC** | 0.211 | 0.304 | 0.282 | 0.068 | 0.158 | 0.207 | **0.766** | | |
| **TEC** | 0.363 | 0.574 | 0.590 | −0.008 | 0.364 | 0.441 | 0.325 | **0.751** | |
| **TTF** | 0.429 | 0.591 | 0.626 | −0.089 | 0.429 | 0.496 | 0.301 | 0.646 | **0.821** |

**Table 6.** Results of reliability and validity.

| | | Indicator Reliability | Convergent Validity | Consistency Reliability | |
|---|---|---|---|---|---|
| Construct | Item | Factor Loading | AVE | Cronbach's Alpha | CR |
| TAC | TAC3 | 0.648 | 0.587 | 0.654 | 0.808 |
| | TAC4 | 0.867 | | | |
| | TAC5 | 0.769 | | | |
| TEC | TEC2 | 0.812 | 0.564 | 0.745 | 0.837 |
| | TEC3 | 0.779 | | | |
| | TEC4 | 0.644 | | | |
| | TEC5 | 0.758 | | | |
| TTF | TTF1 | 0.822 | 0.674 | 0.839 | 0.892 |
| | TTF2 | 0.830 | | | |
| | TTF3 | 0.805 | | | |
| | TTF4 | 0.828 | | | |
| PC | PC1 | 0.773 | 0.583 | 0.764 | 0.847 |
| | PC3 | 0.714 | | | |
| | PC4 | 0.872 | | | |
| | PC5 | 0.682 | | | |
| PE | PE1 | 0.746 | 0.643 | 0.861 | 0.900 |
| | PE2 | 0.719 | | | |
| | PE3 | 0.876 | | | |
| | PE4 | 0.837 | | | |
| | PE5 | 0.821 | | | |
| PR | PR2 | 0.698 | 0.520 | 0.749 | 0.811 |
| | PR3 | 0.645 | | | |
| | PR4 | 0.732 | | | |
| | PR6 | 0.800 | | | |
| PT | PT1 | 0.763 | 0.705 | 0.860 | 0.905 |
| | PT2 | 0.865 | | | |
| | PT3 | 0.866 | | | |
| | PT4 | 0.862 | | | |
| SA | SA1 | 0.860 | 0.731 | 0.908 | 0.932 |
| | SA2 | 0.871 | | | |
| | SA3 | 0.872 | | | |
| | SA4 | 0.833 | | | |
| | SA5 | 0.839 | | | |
| BIU | BIU1 | 0.893 | 0.798 | 0.915 | 0.940 |
| | BIU2 | 0.926 | | | |
| | BIU3 | 0.887 | | | |
| | BIU4 | 0.866 | | | |

### 5.2. Structural Equation Model

To verify the results of the hypothesis, we perform bootstrap and two-tail tests (significance level = 5%) using 5000 samples to obtain the significance level of the path coefficients. As shown in Table 7, a total of 7 of the 11 hypotheses in this proposed model are supported. From the path coefficients, we can see that PC ($\beta = 0.169$, $p < 0.05$), PE ($\beta = 0.144$, $p < 0.05$), SA ($\beta = 0.596$, $p < 0.001$) have significant positive effects on BIU. In addition, PE ($\beta = 0.280$, $p < 0.01$), PC ($\beta = 0.479$, $p < 0.001$) have significant positive effects on SA. The results of the hypothesis structural models is shown in Figure 2.

The effects of TTF, PR and PT on BIU are not significant; however, TTF has an indirect effect on BIU through PE and SA ($\beta = 0.104$, $p < 0.01$) and through PE ($\beta = 0.090$, $p < 0.05$). PE has an indirect effect on BIU through SA ($\beta = 0.167$, $p < 0.01$). In addition, PC also has an indirect effect on BIU via SA ($\beta = 0.285$, $p < 0.001$). TTF has a significant positive effect on PE ($\beta = 0.626$, $p < 0.001$). TEC ($\beta = 0.613$, $p < 0.001$) has a significant positive effect on TTF, while TAC has no such effect.

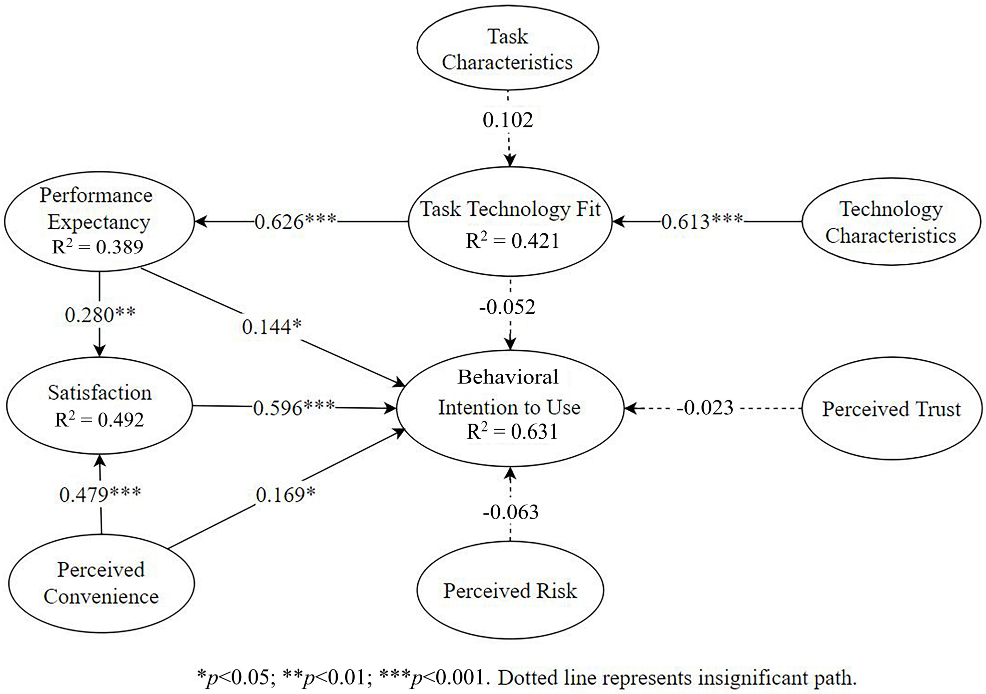


**Figure 2.** Path coefficients.

**Table 7.** Structural model analyses (hypothesis testing).

| Hypotheses | Path | Path Coefficient ($\beta$) | T-Statistics | $f^2$ | $p$-Value | Result |
|---|---|---|---|---|---|---|
| H1 | TAC -> TTF | 0.102 | 1.052 | 0.016 | 0.293 | Not supported |
| H2 | TEC -> TTF | 0.613 | 10.867 | 0.587 | 0.000 | Supported |
| H3 | TTF -> PE | 0.626 | 10.411 | 0.644 | 0.000 | Supported |
| H4 | TTF -> BIU | −0.052 | 0.906 | 0.004 | 0.365 | Not supported |
| H5 | PE -> BIU | 0.144 | 2.070 | 0.023 | 0.038 | Supported |
| H6 | PC -> BIU | 0.169 | 2.399 | 0.030 | 0.016 | Supported |
| H7 | PT -> BIU | −0.023 | 0.392 | 0.001 | 0.695 | Not supported |
| H8 | PR -> BIU | −0.063 | 1.495 | 0.010 | 0.135 | Not supported |
| H9 | SA -> BIU | 0.596 | 8.398 | 0.425 | 0.000 | Supported |
| H10 | PE -> SA | 0.280 | 2.944 | 0.077 | 0.003 | Supported |
| H11 | PC -> SA | 0.479 | 5.191 | 0.225 | 0.000 | Supported |
| **Indirect Path** | | **Path Coefficient ($\beta$)** | **Bca [2.5%, 97.5%]** | | **T-Statistics** | **$p$-Value** |
| TTF -> PE -> BIU | | 0.090 | [0.007, 0.173] | | 2.101 | 0.036 |
| TTF -> PE -> SA -> BIU | | 0.104 | [0.040, 0.193] | | 2.748 | 0.006 |
| PE -> SA -> BIU | | 0.167 | [0.064, 0.294] | | 2.857 | 0.004 |
| PC -> SA -> BIU | | 0.285 | [0.163, 0.413] | | 4.168 | 0.000 |

As presented in Table 7, the effect size $f^2$ is used to measure the effect of the corresponding path independent variable on the dependent variable. According to the threshold values of $f^2$ from Hair [91], we find that the effect sizes of PC and PE on BIU are weak ($0.02 < f^2 < 0.15$). SA has a large effect size on BIU ($f^2 > 0.35$). The effect sizes of PE on SA are weak ($0.02 < f^2 < 0.15$). The effect sizes of PC on SA are medium ($0.15 < f^2 < 0.35$). The effect sizes of TEC on TTF and TTF on PE are strong ($f^2 > 0.35$).

In Table 8, we assess the quality of the proposed model by $R^2$ and $Q^2$, which show the explanatory and predictive effects. Overall, the model predicts 63.1% of the variance of BIU, which has a better explanatory power. In addition, the $Q^2$ values have to be greater than 0, which indicates that the exogenous constructs have predictive relevance for the endogenous construct under consideration [91,92]. Obviously, the $Q^2$ values of the four endogenous latent variables are in line with the requirements.

**Table 8.** $R^2$ and $Q^2$.

| Variables | $R^2$ | Adjusted $R^2$ | $Q^2$ |
|---|---|---|---|
| BIU | 0.642 | 0.631 | 0.496 |
| PE | 0.392 | 0.389 | 0.251 |
| SA | 0.498 | 0.492 | 0.352 |
| TTF | 0.427 | 0.421 | 0.277 |

## 6. Discussion

Except for hypothesis H1, H4, H7 and H8, we can see that the remaining seven proposed hypotheses are supported by the analysis results, which verifies the good fitness of the proposed model. For RQ1, our results show that PC, PE and SA have significant positive effects on BIU of 5G RCS, respectively, among university students. TTF has no significant influence on BIU directly; however, we find that TTF has the indirect impact on BIU through TTF→PE→SA→BIU and TTF→PE→BIU.

TTF is significantly affected by TEC rather than TAC. The reason is that although RCS have outstanding merits compared with the traditional SMS/MMS, the light-spot features (e.g., chatbot, mobile payment, status bar and LBS) have been already used and popular among the existing messaging and OTT apps. Mobile users have alternative ways to finish the specific task. After offline interactive experience, the participant would aware the technique superiority of RCS. Similar to the previous studies [56,65], the path TEC→TTF with strong effect ($f^2$ = 0.587) is verified. Moreover, TTF also has powerful effect on PE ($f^2$ = 0.644).

For the PE, an interesting conclusion is that as the most important predictor in UTAUT model [30], there exists not only a direct path between PE and BIU but also an indirect way among PE→SA→BIU. The reason can be explained that the offline experiment participants could learn the benefits and usefulness of 5G RCS when performing the mobile tasks. Especially, as a competitor among alternative applications (e.g., Alipay, WeChat, MeiTuan) with strong user stickiness, mobile users think the features of RCS would achieve their expectancy and satisfy the personal demands. Moreover, PE also leads to the higher satisfaction towards RCS, which can further improve the mobile users' BIU.

It can be seen that PC is another factor that has a positive impact on the BIU. Different from the previous studies [55,72], this variable imposes not only a direct path on BIU, but also indirect influence to the BIU via SA. The reason is that as an upgraded version of SMS/MMS, RCS integrating chatbots, Plugins, AI applications can provide sufficient functions merely through a single messaging port. Those advanced features will bring convenience to mobile users, especially the university participants after offline experiments. To some extent, it is no longer necessary to download and install the redundant OTT and messaging apps with the service homogeneity on smartphones, which will save plenty of time and storage space for users.

Moreover, PE and PC both have a positive influence on SA. It is worth noting that SA is the vital determinant to the BIU towards 5G RCS ($f^2$ = 0.425), which is similar to the study of SMS in [47]. Compared with the functions of SMS/MMS, users can obviously feel the technology benefits and convenience brought by the new technologies (e.g., chatbot, voice interaction) of 5G RCS in their experience, which improves their satisfaction and then affects their willingness to use 5G RCS in the future.

As an emerging application, users' awareness of the risks of 5G RCS is inevitable; however, unlike the result of [77,78], our results show that PR has no negative effect on BIU of 5G RCS. On the one hand, the participants used to experience a variety of mobile apps and have a certain degree of understanding about the potential risks (such as data breach and privacy concerns). In this case, their sensitivity may become relatively low. On the other hand, the security of 5G RCS is higher than that of traditional SMS and other OTT apps via real-name registration, which is endorsed by state-owned mobile operators.

Contrary to the studies of [54,74], we found that perceived trust (PT) is the variable that has no direct and indirect effect on BIU. The reason can be explained as follows: trust needs a long-term process of accumulation and interactions [73]. As an emerging application, most participants did not use RCS before our offline experiments, who know less about the function of 5G RCS; therefore, the degree of trust of the participants is not formed in a real situation, and there exists a certain bias. Especially in this offline experiment, the intention to use 5G RCS of participants were not because they had a stable degree of trust in advance. In addition, prior to 5G RCS, the participating students are habituated to the alternative applications (e.g., social media and messaging apps), which reduce the participants' trust sensitivity to 5G RCS and also affect the relationship PT→BIU. So, perceived trust has no effect on the intention to use. In the future, high-frequency usage is needed to continuously cultivate users' trust in terms of reliability, ability and strength of RCS to complete specific tasks, and then carry out follow-up verification. Above all, RQ 2 has been addressed.

*Limitations*

In this paper, there are some limitations: First, due to the impact of COVID-19 and quarantine rules, we only recruited university students as participants to experience 5G RCS. Although those groups are apt to learn emerging techniques and open-minded to new things, the distribution of ages is not sufficient (e.g., this group excludes the middle-aged and elderly people). Second, because of there being fewer RCS-capable mobile phones in China, some people only hear about RCS and never actually use them. We have tried our best to find out the 5G RCS accounts offering various kinds of services and provided an operation guideline of RCS for the participants. Moreover, if something went wrong during the interactions, our lab assistant would help resolve the problem. These kinds of experiences cannot replace the actual usage in daily life. In this way, long-term observation should be considered to obtain the real experience of participants. Finally, this paper lacks the support of qualitative research. As a new application, users have little understanding of 5G RCS in the initial stage. Through the semi-structured interview, we can further learn mobile users' attitudes and real experiences towards 5G RCS. which is a supplement for the quantitative study. For example, the collected contents of the interviewees are coded according to the model framework of the quantitative research. We can verify the hypothesis proposed in this paper and find new discoveries, which contribute to improving the accuracy of the model via qualitative analysis.

## 7. Conclusions

In this paper, we have conducted offline experiments to quantitatively study the influencing factors towards the behavioral intention to use (BIU) of 5G rich communication services (RCS) among university students. We have found that satisfaction, perceived convenience and performance expectancy have directly affected the BIU. Although task technology fit (TTF) imposes no direct impact on BIU, the indirect paths TTF→PE→SA→BIU and TTF→PE→BIU exist, which reveals that BIU is largely determined by satisfaction only when the technique benefit and service quality meet the requirements of mobile users. The perceived trust and perceived risk has no significant impact on BIU, which implies that trust and risk are not key factors affecting the intention to use in the initial stage of RCS, when users focus on the advantages of the new application itself.

In terms of implications in this work, we can see that as an emerging application, RCS integrate the all-in-one features via the messaging port, which enriches the functions and service scopes compared with the original short messaging service and multimedia messaging service. Although RCS will bring great convenience and technique advantage to help mobile users resolve the online tasks, the usage habit still need to be cultivated in order to attract more flow and compete with the existing messaging or over the top applications.

For future work, first, we intend to conduct a semi-structured interview by recruiting 5G RCS users through the combination of online and offline means. The interviewees' usage experience can be further revealed as the supplement of quantitative study. Second, after 5G

RCS has been widely popularized, the large-scale questionnaire can be distributed online to improve the simple size and the diversity of respondents (such as age and profession). Third, we can compare 5G RCS with other competitive messaging apps to explore users' preference and psychological state, so as to provide suggestions for the development of 5G RCS.

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## Abbreviations

The following abbreviations are used in this manuscript:

| | |
|---|---|
| A2P | Application to Person |
| AVE | Average Variance Extracted |
| BIU | Behavioral Intention to Use |
| CR | Composite Reliability |
| HMDs | Head-mounted Displays |
| ICT | Information and Communications Technology |
| MaaP | Message as a Platform |
| MMS | Multimedia Messaging Services |
| OEMs | Original Equipment Manufacturers |
| OTT | Over-the-top Services |
| PC | Perceived Convenience |
| PE | Performance Expectancy |
| PLS | Partial Least Squares |
| PR | Perceived Risk |
| PT | Perceived Trust |
| RCS | Rich Communication Services |
| RFID | Radio Frequency Identification |
| SA | Satisfaction |
| SEM | Structural Equation Modeling |
| SMS | Short Messaging Services |
| TAC | Task Characteristics |
| TAM | Technology Acceptance Model |
| TEC | Technology Characteristics |
| TTF | Task-technology Fit |
| UTAUT | Unified Theory of Acceptance and Use of Technology |

## Appendix A. Items of Constructs and Sources

**Table A1.** Items of Constructs and Sources.

| Items | | Source |
|---|---|---|
| **Task characteristics (TAC)** | | |
| TAC1: I need to use my mobile phone for information inquiry, information sharing, chatting, shopping, mobile payment, etc. | * | T. Zhou et al., 2010 [64] |
| TAC2: I often communicate with relatives, friends, or industry users (such as e-commerce sellers, merchants) online. | * | |
| TAC3: I need to interact with individual or institutional users (such as government, business, etc.) online in time. | | |
| TAC 4: When communicating online, I need to fully express my views by words, pictures, audio and video, location, documents, etc. | | |
| TAC5: I have the needs to handle government affairs, people's livelihood, finance, payment and other services online by the mobile phone. | | X. Wang et al., 2021 [93] |
| **Technology characteristics (TEC)** | | |
| TEC1: 5G RCS has the ability to provide required mobile services (such as mobile payments). | * | T. Zhou et al., 2010 [64] |
| TEC2: 5G RCS has the ability to provide real-time services. | | |
| TEC3: 5G RCS respond timely in information enquiry, business handling or payment. | | S. Brown et al., 2010 [94] |
| TEC4: Using 5G RCS, you can send rich media information such as text, pictures, audio and video, and location, and easily interact with other individuals or industry users. | | |
| TEC5: The services provided by 5G RCS can meet daily needs. | | X. Wang et al., 2021 [93] |
| TEC6: 5G RCS is not capable of providing real-time services. | * | |
| **Task Technology Fit (TTF)** | | |
| TTF1: The services provided by 5G RCS are sufficient, when using functions such as information enquiry, business processing, and mobile payment. | | T. Zhou et al., 2010 [64] |
| TTF2: 5G RCS have the ability to provide precise services. | | |
| TTF3: The media type (audio, video, text), location and other functions provided by 5G RCS can meet my communication needs. | | |
| TTF4: Generally speaking, the services provided by 5G RCS are capable of meeting my daily needs (such as mobile payment, appointment registration). | | |
| **Perceived Convenience (PC)** | | |
| PC1: The interface is simple and easy to operate for sending 5G messages through the SMS portal. | | V. Venkatesh et al., 2003 [30] |
| PC2: It's easy for me to be proficient in using and sending 5G messages. | * | |
| PC3: 5G RCS has the ability to provide similar services that integrate traditional SMS, converged communications (such as WeChat), and converged service apps (such as Alipay) without installing redundant apps. | | M. M. Hossain and V. R. Prybutok, 2008 [57] |
| PC4: Compared with all kinds of mobile software, wechat public accounts and small programs, 5G RCS can help save time and simplify the operation process. | | |
| PC5: I can access information and services anytime and anywhere with the help of 5G messaging chatbot features. | | R. Malik et al., 2021 [55] |
| **Performance Expectancy (PE)** | | |
| PE1: 5G RCS is useful when communicating with individual or institutional users online. | | V. Venkatesh et al., 2003 [30] |
| PE2: It is useful when 5G RCS provides personalized rich media information based on my location and scene. | | |
| PE3: Using 5G RCS services makes life much easier. | | C. W. Hsu et al., 2021 [71] |
| PE4: The use of 5G RCS can improve the efficiency of online services. | | |
| PE5: In general, it is useful to use 5G RCS. | | |
| **Perceived Risk (PR)** | | |
| PR1: When using 5G RCS, I am concerned about personal or private information being leaked or used without my acceptance. | * | Z. Yu et al., 2021 [95] |
| PR2: When using 5G RCS, I may receive precise push ads, as well as spam or scam messages. | | K. Al-Saedi et al., 2019 [74] |
| PR3: Rich media messages pushed by 5G RCS may disturb my daily life. | | A. Lawson-Body et al., 2020 [81] |
| PR4: When I use 5G messaging RCS, criminals may steal my private information (such as personal location, identity information, photos, etc.) | | C. Martins et al., 2014 [79] |
| PR5: Learning how to set up and use 5G RCS would probably waste a lot of my time. | * | |
| PR6: At the beginning of commercial use, I think the merchants or scenes covered by 5G RCS are not enough to meet my needs. | | C. M. Chiu et al., 2008 [11] |
| **Perceived Trust (PT)** | | |
| PT1: 5G RCS is generally trustworthy. | | K. Al-Saedi et al., 2019 [74] |
| PT2: 5G RCS can guarantee the reliable transmission of personal, institutional or transaction data. | | |
| PT3: The chatbot service provided by 5G RCS is safe and reliable. | | D. L. Kasilingam, 2020 [96] |
| PT4: The content of information provided by 5G RCS chatbots is reliable to a certain extent. | | R. Pillai et al., 2020 [54] |
| PT5: Overall, 5G RCS services are not trustworthy. | * | |

**Table A1.** *Cont.*

| Items | Source |
| --- | --- |
| **Satisfaction (SA)**<br>SA1: I like to use 5G RCS to complete information enquiry, chatting and business handling efficiently.<br>SA2: I am very satisfied with the real-time service provided by 5G RCS.<br>SA3: I am very content with the accurate and personalized service provided by 5G RCS.<br>SA4: I am quite pleased with the type of rich media messages provided by 5G RCS.<br>SA5: Compared with SMS, wechat official account and various service applications, I think "one-stop service" makes me satisfied by using 5G RCS. | C. M. Chao, 2019 [18]<br>L. Li et al., 2021 [97]<br>D. H. Huang et al., 2021 [72] |
| **Behavioral Intention to Use (BIU)**<br>IU1: I plan to continue using 5G RCS services.<br>IU2: I'm going to often use 5G RCS in the future.<br>IU3: I would recommend 5G RCS to others.<br>IU4: In mobile scenarios, when there are multiple channels such as Wechat, client, mini program, web page and 5G RCS, I will consider using 5G RCS to handle business. | V. Venkatesh et al., 2003 [30]<br>Z. Yu et al., 2021 [95]<br>C. S. Yu, 2012 [13] |

Note : * indicates the deletion of the items in pre-test.

## Appendix B. Operation Accounts List in Offline Experiment

**Table A2.** Operation accounts list of 5G RCS.

| Category | RCS Account Name | Operation |
| --- | --- | --- |
| Government | Tianhe Government Affairs-Intelligent consultation | 1. Make an appointment to apply for an ID card<br>2. Make an appointment for registered enterprises<br>3. Make an appointment for vaccination |
| Life | Beijing_114 | 1. Make an appointment for hospital registration<br>2. Inform to move the car |
| | CTRIP | 1. Buy train tickets, air tickets (voice input)<br>2. Book a hotel |
| | Jiaying Information | 1. Make an appointment for a haircut.<br>2. Make a reservation at the restaurant.<br>3. Book movie tickets |
| Bank | 5G RCS of Hangzhou Bank | 1. Check the account balance<br>2. Pay for water, electricity and coal<br>3. Mobile phone card recharge |
| Enterprise | Great Wall Motor | 1. Online car selection |
| News | Shun Network | 1. Browse the news<br>2. Provide news clues |

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