# Quantify the Behaviour Intention of Individuals to Control SC Performance by Exploring Cloud Storage Services:

## An Extended UTAUT2 Approach

K. A. Asraar Ahmed, VIT-AP School of Business, VIT-AP University, Amaravati Campus, Andhra Pradesh, India
https://orcid.org/0000-0002-8939-7010

Anoop Kumar Sahu, Guru Ghasidas Vishwavidyalaya (Central), Bilaspur, India*

Atul Kumar Sahu, Guru Ghasidas Vishwavidyalaya (Central), Bilaspur, India

Nitin Kumar Sahu, Guru Ghasidas Vishwavidyalaya (Central), Bilaspur, India

## ABSTRACT

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) is explored as a theoretical background to build extended UTAUT2 model with relevant variables for examining the cloud storage services technology acceptance at individual level to respond the current and future SCM operations. The research employed purposive sampling method for data collection. The questionnaire is distributed in booklet format to participants who had experienced in using online cloud storage service platforms (e.g., Google Drive, Microsoft One Drive, etc.). The data are collected from participates dwelling at Chennai metropolitan in South India. The data is analysed by using structural equation modelling technique through Smart PLS 2 software. The performance expectancy, social influence, trust, and perceived speed of access are found to be the strong significant determinants affecting and changing the behavioural intention of individual (customers) towards using cloud storage service technology in managing own firm SCM networks and operations.

## KEYWORDS

Cloud Computing, Supply Chain Management (SCM), Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

## 1. INTRODUCTION

SC is a network, which includes data/information storage, dissemination and serving by individuals/peoples/employees amongst many inbounded and out bounded operations of SC in firm. The supply chain management deals with data storage devices, which reserve information across many SC operations of inside and outside to add monetary value in of industries. Recently, it is realized that a cloud data storage service such as Software as a Service (SaaS), Platform as a Service (PaaS),

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*Corresponding Author

Infrastructure as a Service (IaaS),Function as a Service (FaaS), Machine Learning as a Service (MLaaS) etc. changed industries and enabled individuals/peoples/employees to manage SC operations, due to its huge advantages over traditional storage systems. The cloud storage aid user's industries to securely store or share data without any apprehension towards loss of data. The major benefit of cloud storage is that the sufficient amount of data can be stored without carrying any physical data storage device. Marston et al (2011) defined it as "an information technology service model where computing services (both hardware and software) are delivered on-demand to customers over a network in a self-service fashion, independent of device and location. The resources required to provide the requisite quality-of-service levels are shared, dynamically scalable, rapidly provisioned, virtualized and released with minimal service provider interaction. User's industries pay for the service as an operating expense without incurring any significant initial capital expenditure, with the cloud services employing a metering system that divides the computing resource in appropriate blocks" (p.177). There are many different deployment models of cloud computing exists like 1.) Software as a service (SaaS), 2. Platform as a Service (PaaS), 3. Infrastructure as a Service (IaaS), 4. Function as a Service (FaaS), and 5. Machine Learning as a Service (MLaaS) (see Table 1). This research focuses only on SaaS based cloud services. SaaS cloud is defined as "application or function made available to customers, by the provider, through various devices like web browser or program interfaces" (Wease et al., 2018, p.449).The Software as a Service (SaaS) based cloud storage drives like Google Drive, iCloud, DropBox, Microsoft OneDrive, or Office 365, …etc., which are safe to store and access the data from anywhere, at any place without any complexity(Kalim et al., 2020, Chae, et al., 2020, Chege et al., 2020, Reilly and Milner, 2020, Sahu and Khandekar, 2020, Kani et al., 2020).

The internet industry in India will surge to 160 billion dollars by the year 2025(Goldman Sachs Report, 2019). According to Gartner report (2018) the SaaSbased cloudmarket will reach a worth of $117.1 billion worldwide by the year 2021. Forrester report (2018) predicted that more than half of the enterprises in the world will rely on cloud platform by the year 2018 for enterprise related data storage. According to the Forbes (2018) more than 80% of the entrepreneur's workload will be transformed into cloud by the year 2020 India has second largest cloud storage service user's industries next to China (Gartner Report, 2018); According to Statista report (2017) the Indian cloud storage market is expected grow to a worth of $ 4.28 million by the end of the year 2021.According to NASSCOM Report (2019) predictions India will spend 2.3-2.4 million US dollars by the end of the year 2022. Public cloud will contribute $ 100 billion dollars in India's Gross Domestic Product growth cumulatively by the year 2023 (BCG and Google Analytics, 2019). According to BCG report (2019) India is the third largest public cloud market in Asia Pacific. The cloud storage services have several advantages in terms of cost, scalability, flexibility in storing and sharing the data. There are many challenges associated with cloud computing usage like privacy (PRIV), security (SEC) (Alizadeh et al., 2020: Ratten, 2020,Yaokumah & Amphonsa, 2019), and perceived risk (PCRK) (Ali, 2020, Ratten,2020,Chen et al., 2017; Priyadarshinee et al., 2017), The major positive determinants that drives the usage of cloud storage platforms are performance expectancy (PFIT) (Shahzad et al., 2020), Social Influence (SOIN) (Asadi et al., 2020), Personal Innovativeness (PINV) (Priyadarshinee et al., 2017), Facilitating conditions (FTCN) (Njenga et al., 2019), self-efficacy (Asadi et al., 2020, Arpaci, 2017), Habit (Yaokumah & Amponsah, 2019) and Price Value (Qasem et al., 2019). The mobile and internet technology is surging in India at a rapid phase. It is important to understand the usage of cloud computing at individual user's industries level. The cloud computing usage at individual level is still in a nascent stage in India (Priyadarshinee, 2020a, Priyadarshinee, 2020b, Priyadarshinee et al., 2017). There is a limited in storage space provided for free user's industries in SaaS based cloud platforms like Google Drive, iCloud, DropBox, Microsoft OneDrive, or office 365 etc., (see Table 2). It is important to understand the cloud computing adoption at individual level because it will increase the business performance (Ratten, 2020; Priyadarshinee, 2020a, Priyadarshinee, 2020b).

From the review of literature, it can be observed that there is a dearth of studies on Cloud Computing Storage Service (CCSS) acceptance at individual level in the context of managing SC

**Table 1. Cloud Computing Models in industries for controlling SC operations**

| S.No. | Cloud Service Model | Definition | Examples | Sources |
|---|---|---|---|---|
| 1. | Software as a Service (SaaS) | An application or function made available to customers, by the provider, through various devices like web browser or program interfaces" | Google Drive, i-Cloud, DropBox, Microsoft OneDrive, Office 365 | (Wease*et al.,* 2018, p.449). |
| 2. | Platform as a Service (PaaS), | This service model allows customers to create and run their own software using the provider platform, including systems and environments, to support end-to-end developing, testing, and running of software" | AWS Elastic Beanstalk, Windows Azure, Force.com, and Google App Engine, | Wease*et al.,* 2018, p.449 |
| 3. | Infrastructure as a Service (IaaS), | It is the delivery of hardware (server, storage and network), and associated software (operating systems virtualization technology, file system), as a service. The service provider owns the equipment and is responsible for housing, running and maintaining it". | Digital Ocean, Rackspace, Amazon Web services, and Cisco MetaCloud | Bhardwaj et al (2010) (p.62) |
| 4. | Function as a Service (FaaS), | It is a form of server less computing that manages the resources, lifecycle, and event-driven execution of user's industries-provided cloud functions. The FaaS model lets developers compose applications using cloud functions, and as a result, enabling easy and effective operational cloud control for the provider". | AWS Lambda, Oracle Cloud | Van Eyk et al (2018) p.21 |
| 5. | Machine Learning as a Service (MLaaS) | "MLaaS is a term used for the cloud services that provide automated machine learning models with in-built pre-processing, training, evaluation and prediction modules".<br>&<br>"platform facilitates the creation, validation and execution of machine learning models" | Amazon's Machine Learning Services, Googles Cloud AI Services, and Microsoft Azure Machine Learning Services | Subbiah, U and Ramachandran, M and Mahmood, Z (2019).<br>&<br>Ribeiro *et al* (2015) |

**Table 2. Cloud storage services**

| Name of Platform | Free Storage Space |
|---|---|
| Google Drive | 15 Giga Byte |
| DropBox | 2 Giga Byte |
| Microsoft OneDrive | 5 Giga Byte |
| Apple iCloud | 5 Giga Byte |

operations. Many studies recommended to investigate the effect of Perceived Speed of Access (PSD) (Changchit and Chuchuen, 2016), Personal Innovativeness (PINV) (Shehzad et al., 2020; Asadi et al., 2020), Habit (Song et al., 2020, Yaokumah, &Amponsah, 2019), Trust (TRST) (Ratten, 2020,Njenga et al., 2019, Qasem et al., 2019), and Perceived Risk (PCRK) (Ali, 2020, Ratten, 2020,Wease et al., 2018; Chen aet al., 2017) on behavioural intention of individual in industries towards cloud computing storage services (BICCSS) in managing SC operations. From the literature review, the authors found that major studies on cloud adoption are in organizational setup. The drawback of organizational level has no evidence that individual user's industriesbehaviour towards using the CCSS. Ratten, (2020),Song et al. (2020), Maqueira-Marín et al. (2017) and Wease et al (2018) stipulated that there is a need for more investigation on factors, affecting BICCSS at individualuser's industries level.In future the data storage will completely shift to cloud platform and it is important to know how it is used at individual level (Ratten, 2020, Song et al., 2020, Maqueira-Marín et al., 2017 and Wease et al., 2018).Thus, this motivated to our research to analyse the adoption of cloud services at individual level.To the best of our knowledge,a few studies are carried out on cloud storage services in the country like India, in particular CCSS adoption at individual level. Thus, the objective of research is to identify the factors that change and affect BICSS at the individual level.Thisresearch work is comprised of eight sections. Section 2. consist of Theoretical Background, 3. Literature Review, 4. Research Methodology, 5. Data Analysis and Interpretation, 6. Resultand managerial implications,7. Theoretical Contributions and 8. Limitations and Future Research.

## 2. THEORETICAL BACKGROUND

### 2.1 Unified Theory *o*f Acceptance *a*nd Use *o*f Technology 2 (Utaut2)

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) theory is developed by Venkatesh *et al.* (2012) to understand the technology adoption in consumer context. The UTAUT2 theory is known for its high explanatory power (Venkatesh *et al.,* 2012, Slade*et al.,* 2014; Kranthi and Ahmed, 2018; Alalwan *et al.,* 2017, Yaokumah, &Amponsah, 2019). The UTAUT2 is an extended version of the UTAUT1 model (Venkatesh *et al.,* 2003). The UTAUT1 model has the four major exogeneous variables such as performance expectancy (PFEY), effort expectancy (EFEY), Socialinfluence (SOIN) and facilitating conditions (FTCN). The exogenous variables such as hedonic motivation (HDMN), price value (PVAL) and habit (HABT) are incorporated in the UTAUT2 model. Venkatesh, Thong and Xu (2012) strongly recommends to extend their theory with other relevant exogeneous variables, in different context of theresearch and with different culture. Previous studies have used Theory of planned behaviour (TPB) (Chen*et al.,*2017),Technology Acceptance Model (TAM) (Olubunmi*et al.,*2017; Bachleda andOuaaziz, 2017; Changchit, andChuchuen, 2018; Wease*et al.,*2018;Sharma*et al.,*2016; Tarhini*et al.,* 2017), UTAUT1 (AlsmadiandPrybutok, 2018), Pull-push mooring theory (Wu*et al.,*2017), Technology organization environment theory (TOE) (Wease*et al.,*2018; Priyadarshinee*et al.,*2017), UTAUT2 (Song et al., 2020, Nguyen*et al.,* 2014a, Nguyen*et al.,*2014b; Mathur, 2014; Nikolopoulos, andLikothanassis, 2017) in cloud service adoption context. From the literature review we found that there is lack of extension made on to UTAUT2 model in cloud service adoption context. Also, the UTAUT2 model is found to have strong explanatory power in technology adoption studies (Venkatesh et al., 2012; Kranthi & Ahmed, 2018). Therefore, the presented research extends the UTAUT2 model in cloud storage service adoption context with relevant variables.

## 3. LITERATURE REVIEW

In the presented research work, a meta-analytic literature review process is adopted based on Webster and Watson (2002) and Shaikh & Karjaluoto (2015) guidelines. The keywords like cloud computing, adoption, behavioural intention, cloud technology, cloud storage, etc. are used to search the relevant research articles in the research databases like Elsevier, Emerald, Springer, Sage, IEEE, Taylor & Francis, Pro Quest and EBSCO databases.The research also includes the articles of renowned international conferences which are published in IEEE, Springer or Sage etc., Table 3 shows the operational definition of the constructs used in research work. Table 4 shows the detailed review of literature relevant to the cloud computing adoptioncontext. Figure 1 shows the proposed framework.

### 3.1 Performance Expectancy (PFEY)

Performance expectancy (PFEY) is defined as "*the degree to which using technology will provide benefits to consumers in performing certain activities*" (Venkatesh *et al.,*2012, p. 159). The PFEY has been found to be the strongest determinant in founding studies of technology adoption (Davis, 1989; Thompson et al., 1991; Rogers, 1995; Campeau & Higgins, 1995; Venkatesh and Davis, 2000; Venkatesh & Bala, 2008). Th operational definition of PFEY is shown in the table 3. The CCSS has a benefit of storing the data and can be accessed anywhere without carry any physical disk. The user's industries always look for the benefit received from the technology adoption. In the context of CCSS, the PFEY has a major impact on BICCSS among South Korean (Song et al., 2020),Morrocon (Bachleda, &Ouaaziz, 2017), Nigerian (Olubunmi et al., 2017) and USA (Changchit, &Chuchuen, 2018) user's industries. Njenga et al (2019), Weaseet al. (2018), Shahzad et al (2020) and Qasem et al (2019) strongly recommends PFEY on BICCSS for conducting the further research work.Therefore, the hypothesis H1 can be framed as:

**H1:** The PFEY has a significant impact on behavioral intention to use cloud computing storage services (BICCSS).

### 3.2 Effort Expectancy (EFEY)

Effort expectancy (EFEY) is defined as is the "*degree of ease associated with consumers' use of technology*" (Venkatesh *et al.,* 2012, p. 159). The user's industries friendliness of the technology strongly leads to its acceptance (Davis, 1989; Venkatesh & Bala, 2008, Venkatesh et al, 2012). The operational definition of EFEY is shown in the table 3. The CCSS is a simple application through which data can be shared and stored in drag & drop manner without any difficulty. EFEY is a major determinant for the BICCSS at personal level (Wease et al., 2018). In the context of CCSS, the EFEY has a significant relationship towards BICCSS among Iranian (Alizadeh et al., 2020), Pakistani (Shahzad et al., 2020), Ghanaian (Yaokumah&Amponsah, 2019), USA (Changchit, &Chuchuen, 2018), and Turkish (Arpaci, 2017) user's industriess. Therefore, the hypothesis H2 can be framed as:

**H2:** The EFEYhas a significant impact on behavioral intention to use cloud computing storage services (BICCSS).

### 3.3 Social Influence (SOIN)

Social Influence (SOIN) is defined as "*is the extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology*" (Venkatesh *et al.,*2012, p. 159). The recommendations from the friends, colleagues, or family members have strong significant impact on technology adoption (Venkatesh et al., 2012, Taylor & Todd, 1995, Kranthi & Ahmed, 2018). In the context of CCSS, the SOIN has strong significant impact on BICCSS among Iranian (Asadi et al., 2020), Pakistani (Shahzad et al., 2020), Ghanaian (Yaokumah&Amponsah, 2019), Jordanian (Alsmadi, &Prybutok, 2018), Turkish (Arpaci, 2017), Taiwanese (Chen et al., 2017), Malaysians (Al-Sharafi et al., 2017), and Chinese (Wu et al., 2017) user's industries. At a personal user's industrieslevel, the SOIN leads to technology adoption (Kranthi & Ahmed, 2018), Therefore, the hypothesis H3 can be framed as:

**Table 3. Operational definition of the constructs**

| S.No. | Constructs | Operational Definitions |
|---|---|---|
| 1 | Performance Expectancy (PFEY) | Theuser's industries will adopt the cloud storage services like Google Drive, Microsoft One drive, Dropbox… etc. if it provides benefit to them in storing or sharing the data efficiently. |
| 2 | Effort Expectancy (EFEY) | Theuser's industries will adopt the cloud storage services like Google Drive, Microsoft One drive, Dropbox… etc. if it is easy to use in storing or sharing the data. |
| 3 | Social Influence (SOIN) | The user's industries will adopt the cloud storage services like Google Drive, Microsoft One drive, Dropbox… etc. based on the recommendations of their friends, family or colleagues. |
| 4 | Facilitating Conditions (FTCN) | The user's industries will adopt the cloud storage services like Google Drive, Microsoft One drive, Dropbox… etc. based on the resources (such as PC/Mobile) and support (such as Internet, 4G, cloud software support) to store or share the data. |
| 5 | Hedonic Motivation (HDMN) | The user's industries will adopt the cloud storage services like Google Drive, Microsoft One drive, Dropbox… etc. if it is joyful or entertaining to store or share the data. |
| 6 | Price Value (PRVL) | The user's industries will adopt the cloud storage services like Google Drive, Microsoft One drive, Dropbox… etc. if cost of using such technology (i.e., cloud storage service) is low and with maximum benefits (i.e., minimum internet data cost with maximum data uploading capacity). |
| 7 | Habit (HABT) | The user's industries will adopt the cloud storage services like Google Drive, Microsoft One drive, Dropbox… etc. if they have a habit of regularly using it in frequent intervals to store or share the data. |
| 8 | Trust (TRST) | The user's industries will adopt the cloud storage services like Google Drive, Microsoft One drive, Dropbox… etc. if they strongly believe that the cloud service providers will take care of their data securely and confidentially. |
| 9 | Perceived Risk (PCRK) | The user's industries will adopt the cloud storage services like Google Drive, Microsoft One drive, Dropbox… etc. if they strongly believe that they will not have any negative consequences (i.e., like loss of data or Data privacy breach) in future. |
| 10 | Cloud Computing self-efficacy (CCSE) | The user's industries will adopt the cloud storage services like Google Drive, Microsoft One drive, Dropbox… etc. based on their knowledge about the cloud services and ability to handle the data through it". |
| 11 | Personal innovativeness (PINV) | The user's industries will adopt the cloud storage services like Google Drive, Microsoft One drive, Dropbox… etc. if they love to test out new technology. |
| 12 | Perceived Speed of Access (PSD) | The user's industries will adopt the cloud storage services like Google Drive, Microsoft One drive, Dropbox… etc. if the speed of uploading and retrieving data is high. |
| 13 | Behavioural Intention (BICCSS) | The willing to use cloud storage services like Google Drive, Microsoft One drive, Dropbox… etc. |

**Table 4. Literature review**

| Author &Year | Context | Theory | Methodology, Countries, Sample Size and sample characteristics | Findings | Future research & Remarks |
|---|---|---|---|---|---|
| Priyadarshinee, (2020b) | Cloud Computing Adoption | - | The data were collected through qualitative and quantitative form in medium and small enterprises in India | RISK and TRST plays a significant role in CC adoption | Future research should quantify the factors proposed in the research. |
| Hammouri, & Abu-Shanab, (2020) | Cloud Computing Adoption | - | The data were collected from 134 cloud users of Jordan | SQ, PRVL and CCSE had significant impact on CC adoption | Future research should quantify the factors proposed in the research. |
| Lal, Bharadwaj(2020) | Cloud Computing Adoption | DOI & TOE | The data were collected from 334 IT experts in India | TRST, PFET, PRVL and PRCK had a significant impact on CC adoption. | Future research should quantify the factors proposed in the research. |
| Shahzad, Xiu, Khan, Shahbaz, Riaz, & Abbas, (2020). | Cloud Computing Adoption | TOE | The data of 232 are collected from the employees of MOOC in Pakistan. | PFEY, EFEY, PRVL, FTCN, and SOIN are found to be the significant that affect BICCSS. | The effect of extrinsic and Intrinsic motivation on BICCSS can be examined in future. |
| Song, Kim, & Sohn, (2020) | Cloud Computing Adoption | UTAUT2 | The data of 379 are collected from the user's industries of public cloud services in South Kore. | PFEY, EFEY, and HABT are found to be the strong predictors of BICCSS. | The use behavior is analyzed and recommends to extend the UTAUT2 model in CCSS context. |
| Asadi, Abdekhoda, &Nadrian, (2020) | Cloud Computing Adoption | TPB | The data of 240 are collected from the faculties working in the medical universities in Iran. | SEC, PRIV, CCSE, and SOIN are the significant factors that retained in BICCSS questionnaire development. | Need to explore more factors that affect CCSS with different professions. |
| Alizadeh, Chehrehpak, Nasr, &Zamanifard, (2020) | Cloud Computing Adoption | TOE and HOT | The data of 63 are collected from the experts of cloud computing user's industries in Iran. | SEC, PRIV, EFEY, COMP and FTCN are the major factors that affect BICCSS. | Need to understand the BICCSS with different theory like IS system. |
| Yaokumah, &Amponsah, (2019) | Cloud Computing Adoption | UTAUT2 | The data are collected from five industry sectors of Ghana national. | PFEY, HAB, FTCN, EFEY, SOIN and SEC are found to be the major determinants of BICCSS. | Need to understand the BICCSS with different profession. |
| Njenga, Garg, Bhardwaj, Prakash, &Bawa, (2019) | Cloud Computing Adoption | DOI | The data of 64 respondents from various universities in Kenya are collected. The sample consists of Faculties, Staffs and Students. | PSD, FTCN, and CCSE are found to be the major determinants of BICCSS. | Need to explore more factors that affect BICCSS with different professions. |
| Qasem, Abdullah, Jusoh, Atan, &Asadi, (2019). | Cloud Computing Adoption | SDM | Systematic literature review on BICCSS. | PRVL, FTCN, and PSD are proposed as major factors that may affect BICCSS among higher education institutions. | Future research should quantify the factors proposed in the research. |
| Weaseet *al.* (2018). | Cloud Computing Adoption | TAM | A questionnaire using Qualtrics web tool is developed for gathering the responses from the experts of 250 living in South Korea. | SEC is the major significant factor that affects the BICCSS. | Need to explore more factors that affect BICCSS |

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**Table 4. Continued**

| Author &Year | Context | Theory | Methodology, Countries, Sample Size and sample characteristics | Findings | Future research & Remarks |
|---|---|---|---|---|---|
| Changchit, &Chuchuen (2018) | Cloud Computing Adoption | TAM | The data are collected from 585 students of Southern United States University in USA. | PFEY and EFEY are the significant factors that affect BICCSS. | Future research should be conducted at multiple universities and also consider expanding demographics to include non-student subjects and user's industries in various countries. |
| Nikolopoulos, &Likothanassis (2017) | Cloud Computing Adoption | UTAUT2 | The data of 132 are collected from the university students living in Greece. | PFEY, PVAL, HDMN, and SOIN are found to have strong loadings. The EFIY and HABT are found to have medium loadings in factor analysis. | To explore more factors that affects CCSS with larger samples. Need to analyze the relationship with strong multivariate analysis tools. |
| Alsmadi, &Prybutok (2018) | Cloud Computing Adoption | UTAUT | The data is collected from 129 Jordanian working professionals using a survey-based methodology. | SOIN, SEC, and PRIV are found to be the most significant factors that affect BICCSS. | Need to examine the BICCSS with different professional. |
| Arpaci (2017) | Cloud Computing Adoption | TAM | The data is collected from 221 undergraduate students living in Turkey. | PFEY, EFEY, SOIN, CCSE and PINV are found to be significant on BICCSS. | Need to examine with different professional on BICCSS. |
| Maqueira-Marín, Bruque-Cámara, &Minguela-Rata, (2017) | Cloud Computing Adoption | SDM | The data of 281 samples are collected through telephonic interview with top designated employees (like CEO, CFO) of various industries in Spain. | PFEY and FTCN are found to be significant on BICCSS. | Need more investigation on BICCSS among non-high-tech companies. |
| Chen et al (2017). | Cloud Computing Adoption | TPB, TAM and DOI model | Data for researches are collected from 1069 user's industries in Taiwan and are tested against the relationships through structural equation modeling | CCSE, PCRK, SOIN and COMP are significant factors that affect BICCSS. | Future research could consider applying the UTAUT model proposed by Venkatesh et al. (2003) and a cross-country comparison would be appreciable. |
| Al-Sharafi, Arshah, & Abu Shanab, (2017). | Cloud Computing Adoption | TOE | An email interview method with Sample size of twenty-three experts (nine IT practitioners and fourteen academics) of Malaysia. | PRVL, SOIN, COMP and TRST are the major significant factors that leads to CINT towards CCSS. | Need for more research on CINT. |
| Olubunmi et al. (2017). | Cloud Computing Adoption | TAM | Purposively sampling is drawn from 120 lecturers of Nigeria. | PFEY is found to most significant factor that affect BICCSS. | There is need for more research on BICCSS with different culture. |
| Bachleda, &Ouaaziz, (2017). | Cloud Computing Adoption | TAM | The purposive sampling of 555 respondents are collected from the user's industries of Morocco. | PFEY is found to the most significant factor for BICCSS. | There is a need for more research on BICCSS with different culture. |

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**Table 4. Continued**

| Author &Year | Context | Theory | Methodology, Countries, Sample Size and sample characteristics | Findings | Future research & Remarks |
|---|---|---|---|---|---|
| Priyadarshinee, Raut, Jha, &Gardas, (2017). | Cloud Computing Adoption | TOE | Data are collected from 660 professional experts living in India. | PCRK, OINV, and TRST are found to be significant. | Need to examine with different professional and in consumer context. |
| Wu et al. (2017). | Cloud Computing Adoption | TAM, ECM. DTPB | Questionnaire with online link and sample size is 371 in the country China. | PCRK, TRST and SOIN are significant factors leading to switch to another cloud platform. | Need for more studies on different purpose of cloud computing usage. |
| Kasemsap (2016) | Cloud Computing Adoption | ICT and TOE | Review | RADV, COMP, FCON, INNO and HAB play a major role in BICCSS. | Need for more studies on different purpose of cloud computing usage. |
| Sharma, Al-Badi, Govindaluri, & Al-Kharusi (2016) | Cloud Computing Adoption | TAM | The purposive sampling of 101 are collected from the IT employees of Oman. | PFEY, EFEY, CCSE, and TRST are significant. | Future studies can use UTAUT model for better understanding on the factors impacting BICCSS. |
| Gangwar, Date, & Ramaswamy (2015). | Cloud Computing Adoption | TAM-TOE | The purposive sampling of 280 are collected from the IT experts living in India. | PFEY, COMP, EFEY, CCSE, and FTCN are found to be the significant factors that affect BICCSS. | The research is limited to organizational context. |
| Lian (2015). | Cloud Computing Adoption | UTAUT2 | The research employed the online questionnaire survey approach with the convenience sampling method. The data of 80 is collected from Taiwanese user's industries. | EFEY, SOIN, PCRK and TRST have significant impact on adoption of Cloud-invoicing. | Future studies should apply UTAUT2 model for better explanation in different usage context. |

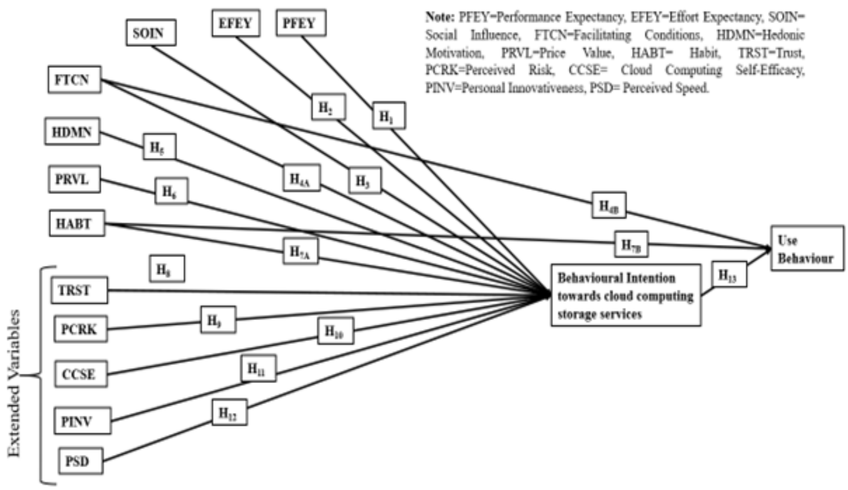
Note: BICCSS= Cloud Computing Self-Efficacy, ISS= Information Success System,CINT= Continues intention, PFEY= Performance Expectancy, EFEY=Effort Expectancy, PRVL= Price Value, SOIN= Social Influence, SQ=Service Quality, PINV= Personal Innovativeness, OINV=Organizational Innovativeness, FTCN=Facilitating Conditions COMP= Compatibility, PCRK= Perceived Risk, PRV= Privacy, INNO= Innovativeness, COMP= Compatibility, TAM= Technology Acceptance Model, RADV=Relative Advantage, ECM= Expectation Confirmation Model, DTPB= Decomposed Theory of Planned Behaviour, TOE=Technology Organization Environment Model, SDM= Self Developed Model, ICT= Information and Communication Technology, TOE=Technology Oriented Environment, HOT= Human Organization and Technology Fit Model, UTAUT= Unified theory of Acceptance and Use of Technology, SDM= Self Developed Model, DOI= Diffusion of Innovation.

**H3:** The SOIN has a significant impact on behavioral intention to use cloud computing storage services (BICCSS).

## 3.4 Facilitating Conditions (FTCN)

Facilitating condition is defined as consumers' perceptions of the resources and support available to perform a behaviour (Venkatesh *et al.,*2012, p. 159). The FTCN is a significant determinant in any technology adoption because a person may have knowledge and skills to use technology but if it is not supported by device or technology resources like internet then it becomes a challenge. The FTCN is also a strong predictor of technology usage behavior (Venkatesh et al., 2012). In order to use CCSS, the devices like the desktop, mobile or tablet with internet connectivity and a minimum bandwidth is required. In the context of CCSS, the FTCN has a significant impact on BICCSS among Pakistani (Shahzad et al., 2020), Ghanaian (Yaokumah&Amponsah, 2019), Kenyan (Njenga*et al.,* 2019), and Spanish (Maqueira-Marín et al. 2019)user's industries. Qasem*et al.,* (2019) in their framework recommends to analyse the effect of FTCN on BICSS at personal user's industries level.

**Figure 1. Proposed framework**




The FTCN is found to be the major predictor of cloud computing use behaviour among Vietnamese user's industries (Nguyen et a., 2014). Therefore, the hypotheses H4A and H4B can be framed as:

**H4A:** The FTCN has a significant impact on behavioral intention to use cloud computing storage services (BICCSS).
**H4B:** The FTCN has a significant impact on use behaviour of cloud computing storage services.

### 3.5 Hedonic Motivation (HDMN)

Hedonic motivation (HDMN) is defined as Hedonic motivation is defined as the fun or pleasure derived from using technology" (Venkatesh *et al.,*2012, p. 161). The joy of using the technology influences the behavioural intention (Venkatesh et al. 2012; Kranthi & Ahmed, 2018). The joy of using technology makes the user's industries feel the easiness of technology and which ultimately leads to its adoption (Venkatesh & Bala, 2008). In the context of CCSS, the HDMN has mixed impact on BICCSS. It differs across context of cloud service usage (Song et al., 2020: Qasem *et al.,* 2019). The HDMN had significant impact on BICCSS among Greece students (Nikolopoulos, & Likothanassis, 2017). The CCSS usage at personal level may have an influence of HDMN because the cloud can be used for storing or sharing the data's like photos or videos which are hedonic in nature. Therefore, the hypothesis H5 can be framed as:

**H5:** The HDMN has a significant impact on behavioral intention to use cloud computing storage services (BICCSS).

### 3.6 Price Value (PRVL)

Price value is defined as "*the cognitive trade-off between perceptions of quality and sacrifice*" (Dodds et al., 1991, p.308). Venkatesh *et al.* (2012) incorporated PRVL in their UTAUT2 model in a mobile technology adoption context by defining it as "*consumers' cognitive trade-off between the perceived benefits of the applications and the monetary cost for using them*" (p.161). The PRVL construct in Venkatesh et al (2012) model defines the cost involved to the consumer to accept the technology. The worthiness of technology is accounted more for its acceptance among user's industries than its cost

(Slade et al., 2014). The research analysis the CCSS usage. The free version of CCSS has a limited capacity of storage (see table 2). The user's industries can opt for the extra storage options by paying premium fee depending the storage requirement. The actual cost involved in using CCSS is with internet technology like Broadband, Wi-Fi or 4$^{th}$ or 5$^{th}$ generation mobile internet. In the context of CCSS, the PRVL has a significant influence on BICCSS among Pakistani (Shahzad et al., 2020), Jordanian (Hammouri, & Abu-Shanab, (2020), Greece (Nikolopoulos, & Likothanassis, 2017), and Malaysian (Al-Sharafi et al., 2017) user's industries. From the literature review we found that majority of studies skipped the PRVL construct because it is conducted in an organization level. Qasem et al (2019) and Song et al (2020) and Hammouri, & Abu-Shanab, (2020)strongly recommended to analyse the influence of PRVL on BICCSSa personal user's industries level. Therefore, the hypothesis H6 can be framed as:

**H6:** The PRVL has a significant impact on behavioral intention to use cloud computing storage services (BICCSS).

## 3.7 Habit (HABT)

The habit has been defined as "*the extent to which people tend to perform behaviours automatically because of learning*" (Limayem*et al.,* 2007, p.705). Venkatesh et al. (2011) defined the HABT as a "*perceptual construct that reflects the results of prior experiences*" (Venkatesh et al., p. 602). The HABT is an important construct of the UTAUT2 model which impacts the behavioral intention and usage of technology and it should not be ignored (Tamilmani et al., 2018). In the context of CCSS, the HABT has a significant influence on BICCSS among Ghanaian (Yaokumah, &Amponsah, 2019), South Korea (Song et al., 2020) and Greece (Nikolopoulos, & Likothanassis, 2017). The impact of HABT construct on technology usage plays a vital role among Indian consumers (Kranthi & Ahmed, 2018). There is lack of research on the impact of HABT towards technology usage behaviour (Qasem et al., 2019, Tamilmani et al., 2018). The HABT is also a strong predictor of use behaviour (Venkatesh et al., 2012, Kranthi and Ahmed, 2018, Tamilmani et al., 2018). Therefore, the hypotheses H7A and H7B can be framed as:

**H7A:** The HABT has a significant impact on behavioral intention to use cloud computing storage services (BICCSS).
**H7B:** The HABT has a significant impact on use behaviour of cloud computing storage services.

## 3.8 Trust (TRST)

Trust is deðned as "whether user's industries are willing to become vulnerable to the online service providers after considering their characteristics (e.g., security, privacy)" (Chong et al., 2012). When it comes to the personal data storage in a technology medium, the TRST factor becomes a major concern for its user's industries. The UTAUT2 model of Venkatesh et al (2012) does not focused on TRST factor because the context of the research is not suitable. The Venkatesh et al (2012) recommended to add relevant variables into the UTAUT2 model. The previous studies which extended the UTAUT2 model with TRST construct isby Slade et al. (2014) in the context of mobile payment adoption. The studies of Kranthi & Ahmed (2018) and Ahmed & Kranthi (2019) extended the UTAUT2 model with TRST factor in the context of smartwatch and mobile ticket adoption respectively. In the context of CCSS, the TRST has significant influence on BICCSS among Iranian (Asadi et al., 2020: Alizadeh et al., 2020), South Koreans (Wease et al., 2018), Jordanian (Alsmadi, &Prybutok, 2018), Malaysian (Al-Sharafi et al., 2017), Indians (Priyadarshinee et al., 2017) and Chinese (Wu et al., 2017) user's industries. There is a need for more investigation on the impact of TRST on CC adoption at individual level (Ratten, 2020:Priyadarshinee, 2020: Ahmed &Sarker, 2020).Therefore, the hypothesis H8 can be framed as:

**H8:** The TRST has a significant impact on behavioral intention to use cloud computing storage services (BICCSS).

### 3.9 Perceived Risk (PCRK)

Perceived risk (PCRK) refers to "certain types of ðnancial, product performance, social, psychological, physical, or time risks when consumers make transactions online" (Forsythe and Shi, 2003, p.869). PCRK also defined as "the user's industries' subjective expectation of suffering a loss in pursuit of the desired outcome" (Pavlou, 2001, p.11). There is always a slight risk involved in any technology. For example, a corrupt desktop may result in loss of data. If the data are stored in the cloud platform and the firewall is not strong enough then it may result in loss data through hacking. The previous studies which extended the UTAUT2 model with PCRK construct is by Slade et al. (2014) in the context of mobile payment adoption. The studies of Kranthi & Ahmed (2018) and Ahmed & Kranthi (2019) extended the UTAUT2 model with TRST factor in the context of smartwatch and mobile ticket adoption respectively. In the context of CCSS, the PCRK has a significant impact on BICCSS among Taiwanese (Chen et al., 2017), Indians (Priyadarshinee et al., 2017), and Omani (Sharma et al., 2016) user's industries. Wease et al. (2018), Ali (2020), Ratten (2020), Ahmed and Sarkar (2020),and Qasem et al. (2019) recommended to analyse the impact of PCRK on BICCSS. Therefore, the hypothesis H9 can be framed as:

**H9:** The PCRK has a significant impact on behavioral intention to use cloud computing storage services (BICCSS).

### 3.10 Cloud Computing Self-Efficacy (CCSE)

Self-efficacy is a belief of a person to perform an act in a given situation (Bandura,1989,1986). Bandura (1986) further defines self-efficacy as "*a person ability to perform a simple/moderate/ difficult task within a particular domain of functioning*" (p.370). Computer task specific self-efficacy, which is defined as "*ability to perform specific computer related tasks in the domain of general computing*" (Agarwal *et al.,* 2000, p.419). Computer self-efficacy is an important determinant of behavioural intention to use technology (Agarwal *et al.,* 2000: Ratten,2013; Kranthi &Ahmed, 2018). The ability of a person to log in to the cloud platform and store the data requires a minimum knowledge on how to use it. For example, in order to upload the data like audio, video, images, pdf, word, etc., the user's industries must log in to his/her account and upload/share the data using options given in the internet cloud platform. This requires knowledge on know-how about the cloud services. In this research work, the self-efficacy will be termed as cloud computing self-efficacy (CCSE) (see table 3). In the context of CCSS, the CCSE has a significant impact on BICCSS among Iranian (Asadi et al., 2020), Jordanian (Hammouri, & Abu-Shanab, (2020), Kenyan (Njenga et al., 2019), Turkish (Arpaci, 2018), Taiwanese (Chen et al., 2017), and Omani (Sharma et al., 2016) user's industries. Song et al (2020) and Qasem et al (2019) and Hammouri, & Abu-Shanab, (2020) strongly recommend to investigate the effect of CCSE on BICCSS. Therefore, the hypothesis H10 can be framed as:

**H10:** The CCSE has a significant impact on behavioral intention to use cloud computing storage services (BICCSS).

### 3.11 Personal Innovativeness (PINV)

Personal innovativeness in information technology (PINV), which is defined as the "*willingness of an individual to try out any new information technology (IT)"* (Agarwal and Prasad, 1998, p.206). To accept the new technology the user's industries must be innovative in his/her thoughts (i.e., to adopt the new technology in a quick time). Innovative personalities do not take much time to accept the new technology (Agarwal and Prasad, 1998). CCSS is the new technology for many user's industries in developing country like India so it this construct plays a significant role in determining the use behavior of CCSS. Kranthi and Ahmed (2018) and Ahmed and Kranthi (2019) extended the UTAUT2 model with PINV construct in the context of smartwatch and mobile ticket adoption respectively. There are very few studies in the context of CCSS, which has investigated the impact of the PINV on BICCSS. To name a few, Arpaci (2017) analyzed the impact of PINV on BICCSS among Turkish, Nguyen et al. (2014) among Taiwanese, Ratten (2016) among (Australian) and Priyadarshinee et al (2017) among Indians. But all those studies are done in an organizational user's industries level not as personal level. Song et al (2020) and Ratten (2020) strongly recommends to analyze the impact of PINV on BICCSS. Therefore, the hypothesis H11 can be framed as:

**H11:** The PINV has a significant impact on behavioral intention to use cloud computing storage services (BICCSS).

### 3.12 Perceived Speed of Access (PSD)

Perceived speed of access is defined as the speed of storing and retrieving the data from the internet (Changchit and Chuchuen, 2016, p.4). The acceptance of cloud technology depends on the speed of the data storage and retrieval (Njenga et al., 2019). Qasem et al. (2019) in their meta-analysis stipulated that the PSD has a significant influence on BICCSS and strongly recommends to analyse the effect of PSD on BICCSS. From the literature review, very few studies have investigated on the impact of PSD towards CCSS in particular.Also, none of the previous studies have incorporated PSD in an UTAUT2 model as an exogeneous variable. Therefore, the hypothesis H12 can be framed as:

**H12:** The PSD has a significant impact on behavioral intention to use cloud computing storage services (BICCSS).

### 3.13 Behavioural Intention to Adopt Computing Storage Services (BICCSS)

The behavioural intention is defined as "the person can decide at will to perform or not perform the behaviour" (Ajzen, 1991, p.142). Behavioural intention is the strongest predictor of use behaviour in technology adoption studies (Davis,1989, Taylor & Todd, 1995, Venkatesh and Davis, 2000, Venkatesh & Bala, 2008, Venkatesh et al., 2012). In the context of CCSS, the BINT has found to be an important determinant of use behaviour among technology user's industries and there is need for more investigation on BICCSS to use behaviour (Song et al., 2020; Alizadeh et al., 2019, Yaokumah, & Amponsah, 2019: Qasem et al., 2019). Therefore, the hypothesis H13 can be framed as:

**H13:** The behavioral intention to cloud computing storage services has a significant impact on use behavior.

## 4. RESEARCH METHODOLOGY

### 4.1 Sample for Research and Data Collection Method

This research employed purposive sampling method for data collection. The questionnaire is distributed in booklet format to all the participants who are aware and experienced in using online cloud platforms like Google Drive, Microsoft One drive, etc. The target samples for research are peoples, who are experienced in using CCSS living in Bengaluru city in south India. According to Barclay *et al.* *(*1995) and Hair *et al.* (2010) the minimum sample size required for the twelve independent variables are one hundred and twenty based on 1:10 ratio (i.e., for one item minimum of ten samples) thumb rule. The research work consists of a valid four hundred and thirty-five samples thus the criteria of the sample size is satisfactory. The data collected method is cross-sectional. The data are collected from the time period of January 2019 to December 2019. The descriptive statistics of the sample are shown in the Table 5.

### 4.2 Variables and Measurement Items

All the measuring instruments are adapted from the previous research works and slightly modified to suit the context of presented research work. The adapted instruments are shown in Table 9 in the Appendix. The questionnaire is designed in two parts. The first part consists of socio-demographic details and the second part consist of statements related to constructs with ‘5’ point Likert scale rating. The partial least square (PLS) method is used for structural equation modelling analysis. Apart from demographic details, all the items are measured using ‘5’ point Likert scale wherein ‘1’ denotes strongly disagree and ‘5’ denotes strongly agree. All the variables have reflective indicators except the use behaviour. The frequency of usage can be measured only in formative type (Venkatesh *et al.,* 2012).

## 5. DATA ANALYSIS AND RESULTS

The variance based structural equation modelling (VB-SEM) through Smart PLS 2 M3 (Ringle *et al.,* 2005) software is used for data analysis. Henseler *et al.* (2009) and Hair *et al.* (2013) recommended to apply the VB-SEM when the model of the research is too complex. If the model of the research

**Table 5. Descriptive statistics**

| | Frequency | Percent |
|---|---|---|
| **Gender** | | |
| Male | 237 | 54.5 |
| Female | 198 | 45.5 |
| **Profession** | | |
| Administrative staff Public | 54 | 12.4 |
| Information Technology Employee Private | 85 | 19.5 |
| Marketing Executive Private | 26 | 5.9 |
| Accountant Executive | 37 | 8.5 |
| Designer Executive | 24 | 5.5 |
| Bank manager Private | 15 | 3.4 |
| HR executive Private | 48 | 11.0 |
| Professor Private | 43 | 9.8 |
| Student Private | 89 | 20.4 |
| Others | 14 | 3.2 |
| **Using Cloud Computing like Google Drive etc. since** | | |
| Less than a year | 117 | 26.9 |
| 1-2 Years | 249 | 57.2 |
| > 3 years | 69 | 15.9 |
| **Total** | **435** | **100.0** |

consists of large number of constructs then VB-SEM is most suitable (Chin, 1998). As per Reinartz *et al.* (2009) and Chin and Newsted (1999) recommendations the VB-SEM is considered as an appropriate method for data analysis when the sample of the research is non-parametric. More importantly when the objective of the research is to extend the existing theory, then using the PLS-SEM is chosen as the best approach (Hair et al., 2011, p.144). PLS-SEM is the most preferred analysis technique when "the model is complex with large number of antecedents' constructs linking to an endogenous construct" (Wu and Chen, 2014, p. 84). Thus, the VB-SEM analysis is carried out using Hair et al., (2011) recommendations. This research work follows two-step method (i.e., measurement model and structural model) of Anderson and Gerbing's (1988) recommendations.

## 5.1 Measurement Model

The measurement model "represents the relationship between constructs and their corresponding indicator variables" (Hair *et al.,* 2013, p.40). The measurement model analysis is essential because it gives clear an idea on the reliability of the constructs used in the research.

### *5.1.1 Assessment of Reliability of the Constructs*

The individual items are assessed for the reliability test based on Bagozzi (2011) criteria which states that '*all the items of each construct should have loadings of above 0.5 value*'. The reliability test consists of two criteria's i) Cronbach's alpha and ii) composite reliability should be greater than 0.7 (Bagozzi, 2011; Hair *et al.,* 2013, Hair *et al.,* 2010) for all the constructs. According to Hair *et al.* (2013) and Bagozzi and Yi (1988) guidelines on PLS-SEM the Cronbach's Alpha and Composite reliability values should be greater than 0.7. The Cronbach's Alpha and Composite reliability are greater than 0.7 hence the constructs used in the research work, are found reliable.

### *5.1.2 Assessment of Validity of the Constructs*

The validity test consists of two criteria's i) Convergent validity and ii) Discriminant validity. The convergent validity is defined as "*the extent to which a measure correlates positively with alternative measures of the same construct*" (Hair *et al.,* 2013, p. 102). Average Variance Extracted (AVE) is the most commonly adopted measures for convergent validity (MacKenzie*et al.,* 2011). The AVE is defined as "*the grand mean value of the squared loadings- of the indicators associated with the construct (i.e., the sum of the squared loadings divided by the number of indicators)*" (Hair *et al.,* 2013, p. 103). The AVE values should be more than 0.50 to have convergent validity (Hair *et al.,* 2013; Fornell and Larcker, 1981; MacKenzie*et al.,* 2011). All the constructs having AVE values above 0.5 which satisfies the thumb rule of Hair *et al.* (2013, p. 103). Discriminant Validity is defined as "*the extent to which a construct is truly distinct from other constructs by empirical standards*" (Hair *et al.,* 2013, p. 105). In the research work, the Fornell and Larcker (1981) approach is used. Under the Fornell and Larcker criterion "*the square root of AVE values should be greater than its highest correlation with any other construct*" (Hair *et al.,* 2013, p. 107). Thus, all the constructs used in the research work are found valid.

## 5.2 Structural Model

The structural model analysis (hypotheses testing) is done to understand the causal relationships between the exogeneous and endogenous variables (Hair *et al.,* 2013, p. 168). The structural model is assessed using the five-step procedure of Hair *et al.* (2013).

### *5.2.1 Step 1: The Collinearity Test*

The collinearity test is carried out based on variance inflation factor (VIF) value (i.e., VIF < 5) to ensure that there are no high standard error values among the exogenous variables. Variance inflation factor (VIF) is defined as "*the degree to which the standard error has been increased due to the presence of collinearity*" (Hair *et al.,* 2013, p. 124). The collinearity test shows that all the exogeneous

**Table 6. Data analysis**

| Constructs | Items | Loadings | AVE | Composite Reliability | R Square | Cronbach's Alpha |
|---|---|---|---|---|---|---|
| BICCSS | BICCSS1 | 0.941 | 0.814 | 0.929 | 0.752 | 0.885 |
| | BICCSS2 | 0.922 | | | | |
| | BICCSS3 | 0.841 | | | | |
| PFEY | PFEY1 | 0.897 | 0.757 | 0.903 | | 0.845 |
| | PFEY2 | 0.820 | | | | |
| | PFEY3 | 0.892 | | | | |
| EFEY | EFEY1 | 0.857 | 0.779 | 0.934 | | 0.906 |
| | EFEY2 | 0.910 | | | | |
| | EFEY3 | 0.886 | | | | |
| | EFEY4 | 0.876 | | | | |
| SOIN | SOIN1 | 0.904 | 0.785 | 0.916 | | 0.863 |
| | SOIN2 | 0.891 | | | | |
| | SOIN3 | 0.862 | | | | |
| FTCN | FTCN1 | 0.865 | 0.701 | 0.903 | | 0.860 |
| | FTCN2 | 0.883 | | | | |
| | FTCN3 | 0.864 | | | | |
| | FTCN4 | 0.728 | | | | |
| HDMN | HDMN1 | 0.841 | 0.740 | 0.895 | | 0.823 |
| | HDMN2 | 0.929 | | | | |
| | HDMN3 | 0.806 | | | | |
| PRVL | PRVL1 | 0.877 | 0.762 | 0.906 | | 0.845 |
| | PRVL2 | 0.851 | | | | |
| | PRVL3 | 0.890 | | | | |
| HABT | HABT1 | 0.876 | 0.750 | 0.900 | | 0.833 |
| | HABT2 | 0.816 | | | | |
| | HABT3 | 0.903 | | | | |
| TRST | TRST1 | 0.899 | 0.771 | 0.931 | | 0.900 |
| | TRST2 | 0.901 | | | | |
| | TRST3 | 0.821 | | | | |
| PCRK | PCRK1 | 0.938 | 0.878 | 0.935 | | 0.861 |
| | PCRK2 | 0.936 | | | | |
| CCSE | CCSE1 | 0.859 | 0.779 | 0.934 | | 0.907 |
| | CCSE2 | 0.882 | | | | |
| | CCSE3 | 0.940 | | | | |
| | CCSE4 | 0.847 | | | | |

*continued on following page*

**Table 6. Continued**

| Constructs | Items | Loadings | AVE | Composite Reliability | R Square | Cronbach's Alpha |
|---|---|---|---|---|---|---|
| **PINV** | **PINV1** | 0.887 | 0.778 | 0.933 | | 0.904 |
| | **PINV2** | 0.818 | | | | |
| | **PINV3** | 0.914 | | | | |
| | **PINV4** | 0.906 | | | | |
| **PSD** | **PSD1** | 0.843 | 0.695 | 0.901 | | 0.854 |
| | **PSD2** | 0.821 | | | | |
| | **PSD3** | 0.846 | | | | |
| | **PSD4** | 0.824 | | | | |

variables have VIF values less than 5 which indicates there is no multi-collinearity between the exogenous variables. The common method bias (CMB) test is done based on Podsakoff, Mackenzie, Lee, & Podsakoff, (2003) recommendations and also Venkatesh *et al.* (2012) strongly recommended to analyse CMB test for UTAUT2 model. The Harman's one factor test is used for CMB test and the results showed (Maximum 22.3%) that there is no significant CMB in our dataset. According to Knock (2015) the Variance Inflation Factor (VIF) the VIF values should not be greater than 3.3 (p.7). Thus, the model can be considered as free of common method bias.

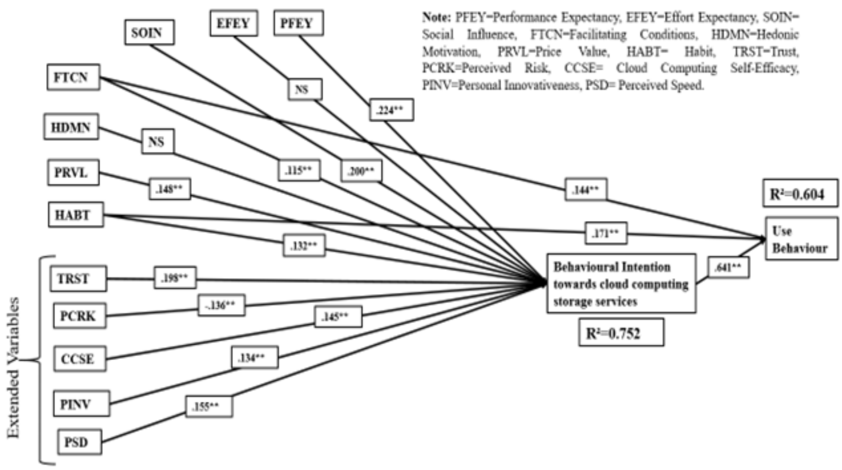
### *5.2.2 Step 2: Evaluation of Hypothesized Path Coefficient Using Bootstrapping Technique*

The hypothesised path coefficients (β) are assessed using PLS-SEM algorithm technique through Smart PLS software. The path coefficient values vary from -1 to +1 wherein the path coefficient value close to 1 represents strong positive relationship (Hair *et al.,* 2013, p. 171). As per Hair *et al.* (2013, p.130) procedure the bootstrapping technique which represents "*a large number of subsamples (i.e., boot strap samples) are drawn from the original sample with replacement*" (Hair *et al.,* 2013,

**Table 7. Discriminant validity using Fornell and Larcker (1981) method**

| | BICCSS | CCSE | EFEY | FTCN | HABT | HDMN | PFEY | PCRK | PSD | PRVL | PINV | SOIN | TRST |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **BICCSS** | **0.902** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **CCSE** | 0.382 | **0.882** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **EFEY** | 0.485 | 0.094 | **0.882** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **FTCN** | 0.362 | 0.151 | 0.308 | **0.837** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **HABT** | 0.330 | 0.117 | 0.292 | 0.086 | **0.866** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **HDMN** | 0.276 | 0.008 | 0.192 | 0.102 | 0.098 | **0.860** | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **PFEY** | 0.676 | 0.314 | 0.377 | 0.241 | 0.243 | 0.233 | **0.870** | 0 | 0 | 0 | 0 | 0 | 0 |
| **PCRK** | -0.501 | -0.197 | -0.244 | -0.236 | -0.171 | -0.136 | -0.448 | **0.937** | 0 | 0 | 0 | 0 | 0 |
| **PSD** | 0.388 | 0.088 | 0.151 | 0.185 | 0.088 | 0.181 | 0.153 | -0.254 | **0.833** | 0 | 0 | 0 | 0 |
| **PRVL** | 0.423 | 0.169 | 0.349 | 0.167 | 0.195 | 0.168 | 0.355 | -0.139 | 0.065 | **0.873** | 0 | 0 | 0 |
| **PINV** | 0.377 | 0.257 | 0.279 | 0.231 | -0.093 | 0.037 | 0.189 | -0.217 | 0.295 | 0.085 | **0.882** | 0 | 0 |
| **SOIN** | 0.479 | 0.150 | 0.376 | 0.031 | 0.111 | 0.206 | 0.366 | -0.215 | 0.102 | 0.244 | 0.094 | **0.886** | 0 |
| **TRST** | 0.478 | 0.010 | 0.290 | 0.121 | 0.143 | 0.070 | 0.445 | -0.206 | 0.174 | 0.095 | 0.169 | 0.214 | **0.878** |

**Figure 2. Structural equation Model PLS output**




P.130) is used to estimate PLS path model. The significance levels of the hypothesized path are evaluated using bootstrapping techniques with 5000 bootstrap samples and no sign change option is used as per thumb rule of Hair et al (2013, p. 138). As per thumb rule of Hair *et al.* (2013, p. 127), the t-values for two tail test ranges from t=1. 56 (α=0. 10), t=1. 96 (α=0. 05), and t= 2. 57 (α=0. 01). In the conducted research work, 95% of confidence level is considered for hypotheses testing. All the hypotheses are supported except H2 and H5. The hypotheses H1 (PFEY→BICCSS, β=0.224), H3 (SOIN→BICCSS, β=0.200), H4A (FTCN→BICCSS, β=0.115), H4B (FTCN→USB, β=0.144), H6 (PRVL→BICCSS, β=0.148), H7A (HABT→BICCSS, β=0.132), H7B (HABT→USB, β=0.171), H8 (TRST→BICCSS, β=0.198), H10 (CCSE→BICCSS, β=0.145), H11(PINV→BICCSS, β=0.134), H12 (PSD→BICCSS, β=0.155) and H13 (BICCSS→USB, β=0.641) are positively significant at 99.99% of confidence interval with ρ-value < 0.001 and t-statistics above 2.57 towards behavioural intention of cloud computing. The hypothesis H9 (PCRK→BICCSS, β=-0.136) is negatively significant at 99.99% of confidence interval with ρ-value < 0.001 and t-statistics above 2.57 towards behavioural intention of cloud computing. The hypotheses H2 and H5 are not supported with ρ-value > 0.05 at 95% of confidence interval.

### *5.2.3 Step 3: Evaluation of Coefficient of Determination $R^2$*

The coefficient of determination $R^2$is assessed based on Hair *et al.* (2013) and Henseler*et al.* (2009) criteria which states that in marketing research the $R^2$ values a) below 0.25 is considered to be weak, b) above 0.50 is considered to be medium and c) above 0.75 is considered to be high in explanatory power. The $R^2$ value is above 0.75 (i.e.,$R^2$=0.752) on behavioural intention towards cloud computing adoption, which indicates that the proposed model has high explanatory power. The $R^2$ value on use behaviour is above 0.50 (i.e., 0.604) which shows that it has medium explanatory power.

### *5.2.4 Step 4: Evaluation of Effect Size $f^2$*

The effect size $f^2$is assessed based on Henseler*et al.* (2009) and Chin (1998) criteria which states that the $f^2$ values ranges between 0.02-0.14, 0.15-0.34 and above 0.35 is considered to have a low, medium and high effect on exogeneous variable respectively. The $f^2$ effect size "*analyses how much a predictor construct contributes to the $R^2$ value of a target construct in the structural model*" (Hair *et al.,* 2013, p.198). The $f^2$ values are shown in Table 8. Step v) The evaluation of predictive relevance $Q^2$ and effect size $q^2$ using blindfolding procedure.

**Table 8. Path coefficient and effect size**

| Path | β-Coefficient | t-statistics | ρ-value | Hypothesis | $f^2$ effect size | $q^2$ effect size |
|---|---|---|---|---|---|---|
| PFEY ->BICCSS | 0.224 | 5.890 | ** | H1 | 0.105 | 0.050 |
| EFEY -> BICCSS | 0.022 | 0.782 | NS | H2 | 0.000 | 0.000 |
| SOIN ->BICCSS | 0.200 | 7.163 | ** | H3 | 0.121 | 0.065 |
| FTCN -> BICCSS | 0.115 | 3.921 | ** | H4A | 0.044 | 0.022 |
| FTCN -> USB | 0.144 | 4.096 | ** | H4B | 0.045 | .026 |
| HDMN ->BICCSS | 0.062 | 1.898 | NS | H5 | 0.004 | 0.002 |
| PRVL ->BICCSS | 0.148 | 5.652 | ** | H6 | 0.069 | 0.035 |
| HABT->BICCSS | 0.132 | 5.038 | ** | H7A | 0.056 | 0.027 |
| HABT ->USB | 0.171 | 5.054 | ** | H7B | 0.066 | .029 |
| TRST ->BICCSS | 0.198 | 6.442 | ** | H8 | 0.117 | 0.058 |
| PCRK ->BICCSS | -0.136 | 4.780 | ** | H9 | 0.056 | 0.027 |
| CCSE ->BICCSS | 0.145 | 5.661 | ** | H10 | 0.069 | 0.032 |
| PINV ->BICCSS | 0.134 | 4.597 | ** | H11 | 0.052 | 0.027 |
| PSD -> BINT | 0.155 | 6.321 | ** | H12 | 0.081 | 0.040 |
| BINT -> USB | 0.641 | 17.749 | ** | H13 | 0.803 | 0.764 |

*= significant at ρ<.05 (95%), **= significant at ρ< .01 (99%), NS= Not Significant.

Note: PFEY=Performance Expectancy, EFEY=Effort Expectancy, SOIN= Social Influence, FTCN=Facilitating Conditions, HDMN=Hedonic Motivation, USB=Use Behaviour, PRVL=Price Value, HABT= Habit, TRST=Trust, PCRK=Perceived Risk, CCSE= Cloud Computing Self-Efficacy, PINV=Personal Innovativeness, PSD= Perceived Speed, BICCSS=Behavioral intention Cloud Computing Storage service, TOE=Technology Oriented Environment, UTAUT= Unified theory of Acceptance and Use of Technology, CINT= Continues intention, PFEY= Performance Expectancy, PRVL= Price Value, SI= Social Influence, COMP= Compatibility, TAM= Technology Acceptance Model, ECM= Expectation Confirmation Model, and DTPB= Decomposed Theory of Planned Behaviour.

The evaluation of predictive relevance $Q^2$ and effect size $q^2$is done based on Geisser (1974), Stone (1974) and Hair *et al.* (2013) procedure which states that $Q^2$ values ranges between 0.02-0.14, 0.15-0.34 and above 0.35 is considered to have a small, medium and strong predictive relevance on exogeneous variable respectively. The $Q^2$ is defined as "*a measure of how well the path model can predict the originally observed values*" (Hair *et al.,* 2013, p.183). The $Q^2$ value on reflective endogenous variable behavioural intention is $Q^2$=0.604 which indicates that behavioural intention has a strong predictive relevance. Blindfolding is defined as a "*sample reuse technique that omits every $d^{th}$ data value from the endogenous constructs indicators and estimates the parameters with the remaining data points*" (Hair *et al.,* 2013, p. 178). The cross-validated redundancy method is used as per the guidelines of (Hair *et al.,* 2013, p. 183). The effect size $q^2$ are shown in Table. The effect size $q^2$ values ranges between 0.02-0.14, 0.15-0.34 and above 0.35 is considered to have a small, medium and strong predictive relevance for certain exogeneous variable respectively (Hair *et al.,* 2013, p.184).

The presented research work extended the UTAUT2 model by incorporating variables such as trust (TRST), perceived risk (PCRK), cloud computing self-efficacy (CCSE), personal innovativeness (PINV), and perceived speed of access (PSD). The total variance explained on behavioural intention (BI)is $R^2$=75.2% and on use behavior (USB) is $R^2$= 60.4%. The hierarchy of variables which accounts for causing variance in BINT are PFEY (β=0.224), followed by SOIN (β=0.224), TRST (β=0.200), PSD (β=0.155), PRVL (β=0.148), CCSE (β=0.145), PINV (β=0.134), HABT (β=0.132), and FTCN (β=0.115). The PRCK (β= -0.136) has strong negative effect on BINT. The hierarchy variables which account for causing variance in USB are BINT (β=0.148), followed by HABT (β=0.171) and FTCN (β=0.144). The effect size $f^2$justifies the extension of variables in UTAUT2 model. The incorporated variables such as TRST ($f^2$=0.117), PCRK ($f^2$=0.056), CCSE ($f^2$=0.069), PINV ($f^2$=0.052) and PSD ($f^2$=0.117) are having small effect on BINT. Therefore, their inclusion in model extension is justified in Indian cloud service user's industries' context. The predictive relevance $Q^2$ and its effect size $q^2$further justify the relevancy of extended variables in UTUAT2 model. The extended variables such as TRST ($q^2$=0.058), PCRK ($q^2$=0.027), CCSE ($q^2$=0.032), PINV ($q^2$=0.027) and PSD ($q^2$=0.040) are having small predictive relevance on BINT. Therefore, their inclusion for the UTAUT2modelextensionis justified.

## 6. CONCLUSION AND MANAGERIAL IMPLICATIONS

The results conclude that the PFEY, SOIN, TRST, PSD, PRVL, CCSE, PINV, HABT, PCRK and FTCN are found to be the important determinants that affect and changes the BICCSS. Also, the BICCSS, HABT and FTCN are having moderate impact on use behaviors. The research work also shows that the new exogeneous variables as a part of the UTAUT2 model, are found significant for BICCSS (see table 8). The research proposed a new comprehensive framework for analyzing each user's industries behavior towards CCSS, linked to supply chain management. From the findings perspective, a few important implications can be drawn, which benefit the policy makers. The cloud service providers should consider the significant factors must have considerable effect size (see Table 8). The most important predictor for BICCSS is PFEY so the cloud service providers must design their cloud platform with more options like interactive file handling (i.e., upload/download/sharing) by focusing on time saving and benefit aspect. The SOIN is found as a second strongest effect on BICCSS so the cloud service providers must focus on delivering a delightful service experience to their user's industries, which may ultimately result in peer-to-peer promotion. The third strongest element that influences the BICCSS is TRST so the cloud service providers must maintain their application with strong data security and safety against hacking. The fourth important determinant of BICCSS is PSD so the cloud service providers must design their applications, which can be accessed through low-speed internet and with a quick upload/sharing/download facility. In developing country such as India, the cloud platform adoption may increase, if the data are accessed in low internet environment. It can be done through optimization of the cloud application. The next most important determinant is PRVL so the cloud service providers can offer an extra storage space with a low premium or more discounts for the subscribers who opt service for longer time period which may lead to more usage. The next important determinant is CCSE so the cloud service providers must focus on designing the application with more users' industries interactivity and with less complexity. The next element, which affects the BICCSS is PINV so the cloud providers can offer more innovative service options because the user's industries are ready to adopt the innovative features. HABT strongly effected BICCSS and use behavior so the service providers must maintain the relationship with the user's industries by offering loyalty schemes. PCRK negatively impacted the BICCSS which is good sign for service providers so they must maintain the data privacy and security by updating the platform regularly. FTCN have significant effect on BICCSS and use behavior which is good indication for the service providers that their services are accessible and supported with user's industries' devices. Thus, the study concludes that the determinants such as PFEY, SOIN, TRST, PSD, PRVL, CCSE, HABT and PCRK has significant effect on BICCSS users' industries. The cloud service providers must focus on aforementioned determinants and strategize their business.

## 7. THEORETICAL CONTRIBUTIONS

The presented research contributed to the theory by extending the UTAUT2model of Venkatesh *et al.* (2012). This research gains novelty by adding the variables to suit the context of the BICCSS. The variables considered for the model extension are TRST, PCRK, CCSE, PINV, and PSD. From the results obtained in the presented research work, it can be concluded that the proposed extended UTAUT2 model has a great explanatory power. The inclusion of variables accounted for 75.2% of the variance in the behavioural intention and in the use behavior 60.4%.The research supports the stipulation of Venkatesh et al. (2012), Slade et al (2014) and Kranthi & Ahmed (2018) that the UTAUT2 model has the high explanatory power in predicting behavioral intention towards technology acceptance and usage. The research incorporated new relevant variables in the UTAUT2 model with a significant effect size when compared to the previous studies (Song et al., 2020, Priyadarshinee et al., 2017, Nguyen et al., 2014a, Nguyen et al., 2014b; Mathur, 2014; Nikolopoulos, and Likothanassis, 2017) in the context of cloud computing. Thus, the UTAUT2 model is proved to have high explanatory power in the context of CCSS. The research further proves the proposed model with strong predictive relevance and effect size values of the new variables incorporated.

## 8. LIMITATIONS AND FUTURE RESEARCH

The first limitation of presented research is that the sample is limited to a country of India, Bengaluru in particular. The moderating variables of UTAUT2 like gender, age, and experience are not considered therefore future research should analyse the effect of moderators. The sample characteristics are mix of all profession with different proportions. The main reason behind this is because the goal of this research is to identify the determinants that affect CCSS at an individual level. So future research should analyse the behaviour towards CCSS across different professions using probability sampling method. The proposed model is framed based on relevant variables extracted from the meta-analysis of literatures in cloud computing context and may differ across culture. The proposed framework should be tested in future with different culture and sample characteristics to validate the model. According Tamilmani et al. (2018) the habitual behaviour for a technology develops after prolonged usage future studies should focus on longitudinal data collection for measuring habit. (Tamilmani et al, 2018). The future research should also focus on analysing the determinants that affect continue intention towards cloud computing storage services adoption (Al-Sharafi et al., 2017; Song et al., 2020). Also, future research should consider the cross-country comparison on CCSS (Alizadeh et al., 2020, Chen et al., 2017). Future research can integrate the constructs of information system success (ISS) model (Alizadeh et al., 2020) into the proposed model for deeper understanding on behavioural intention towards CCSS. Finally, by applying the proposed model in different countries would bring more interesting insights and supply chain of firm can be balanced.

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## APPENDIX

**Table 9. Adapted instruments**

| Measuring Instruments | Items | Sources |
|---|---|---|
| ***Performance Expectancy*** | | Adapted and slightly modified from (Venkatesh *et al.,* 2012) |
| I find cloud computing services (like Google Drive/ Microsoft One drive/ Dropbox etc.) in my daily life. | **PFEY1** | |
| Using cloud computing services (like Google Drive/ Microsoft One drive/ Dropbox etc.) helps me accomplish things more quickly. | **PFEY2** | |
| Using cloud computing services (like Google Drive/ Microsoft One drive/ Dropbox etc.) increases my productivity. | **PFEY3** | |
| ***Effort Expectancy*** | | Adapted and slightly modified from (Venkatesh *et al.,* 2012) |
| Learning how to use cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.) is easy for me. | **EFEY1** | |
| My interaction with cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.) is clear and understandable | **EFEY2** | |
| I find cloud computing services (like Google Drive/ Microsoft One drive/ Dropbox etc.) easy to use. | **EFEY3** | |
| It is easy for me to become skillful at using cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.). | **EFEY4** | |
| ***Social Influence*** | | Adapted and slightly modified from (Venkatesh *et al.,* 2012) |
| People (friends, family and colleagues) who are important to me think that I should use cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.). | **SOIN1** | |
| People (friends, family and colleagues) who influence my behavior think that I should use cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.). | **SOIN2** | |
| People (friends, family and colleagues) whose opinions that I value prefer that I use cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.). | **SOIN3** | |
| *Facilitating Conditions* | | Adapted and slightly modified from (Venkatesh *et al.,* 2012) |
| I have the resources necessary to use cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.). | **FTCN1** | |
| I have the knowledge necessary to use cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.). | **FTCN2** | |
| Cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.) is compatible with other technologies I use | **FTCN3** | |
| I can get help from others when I have difficulties using Cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.). | **FTCN4** | |
| **Hedonic Motivation** | | Adapted and slightly modified from (Venkatesh *et al.,* 2012) |
| Using Cloud computing services (like Google Drive/ Microsoft One drive/ Dropbox etc.) is fun. | **HDMN1** | |
| Using Cloud computing services (like Google Drive/ Microsoft One drive/ Dropbox etc.) is enjoyable. | **HDMN2** | |
| Using Cloud computing services (like Google Drive/ Microsoft One drive/ Dropbox etc.) is very entertaining. | **HDMN3** | |

*continued on following page*

**Table 9. Continued**

| Measuring Instruments | Items | Sources |
|---|---|---|
| **Price Value** | | Adapted and slightly modified from (Lai and Shi, 2015) |
| Cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.) is reasonably priced. | **PRVL1** | |
| Cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.) is a good value for the money. | **PRVL2** | |
| At the current price, Cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.) provides a good value. | **PRVL3** | |
| **Habit** | | Adapted and slightly modified from (Venkatesh *et al.*, 2012) |
| The use of Cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.) has become a habit for me. | **HABT1** | |
| I am addicted to using Cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.). | **HABT2** | |
| I must use Cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.). | **HABT3** | |
| **Trust** | | Adapted and slightly modified from (Catherine Bachleda and Sanaa Ait Ouaaziz 2017; McKnight, Choudhury, and Kacmar,2002) |
| I feel assured that legal and technological structures on the Internet would adequately protect me from problems with using cloud computing. | **TRST1** | |
| I feel confident that encryption advances (e.g., use of passwords) would make it safe for me to store my data on cloud. | **TRST2** | |
| In general, I believe that cloud would be a robust and safe environment in which to store information. | **TRST3** | |
| **Perceived Speed** | | Adapted and slightly modified from (ChuleepornChangchit and Chat Chuchuen, 2016) |
| I believe that the speed of cloud computing is the same as working on files stored on a traditional laptop or PC. | **PSD1** | |
| I believe that the speed of cloud computing is sufficient for backup and storage. | **PSD2** | |
| I believe that the speed of cloud computing to upload/download files is the same as uploading/downloading to any other Internet website. | **PSD3** | |
| I believe that the speed of cloud computing is sufficient for my everyday work. | **PSD4** | |
| **Cloud Computing Self-efficacy** | | Adapted and slightly modified from (Agarwal *et al.,* 2000; Chau, 2001; Compeau and Higgins, 1995; Lee and Hsieh, 2009; McDonald and Siegall, 1992; Wang and Wang, 2008) |
| I am able to use a cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.) without the help of others | **CCSEF1** | |
| I have the knowledge and skills required to use a cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.) | **CCSEF2** | |
| I am able to use a cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.) reasonably well on my own. | **CCSEF3** | |
| Overall, I am confident in using a cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.) by Myself. | **CCSEF4** | |

*continued on following page*

**Table 9. Continued**

| Measuring Instruments | Items | Sources |
|---|---|---|
| **Personal innovativeness** | | Adapted and slightly modified from Agarwal and Prasad (1998) |
| If I heard about new technology, I would look for ways to experiment with it. | **PINV1** | |
| Among my peers, I am usually the first to explore new information technologies. | **PINV2** | |
| I like to experiment with new information technologies. | **PINV3** | |
| In general, I am hesitant to try out new information technologies. (RC) | | |
| **Behavioural Intention** | | Adapted and slightly modified from (Venkatesh *et al.*, 2012) |
| BI1. I intend to continue using Cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.) in the future. | **BINT1** | |
| BI2. I will always try to use Cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.) in my daily life. | **BINT2** | |
| BI3. I plan to continue to use Cloud computing services (like Google Drive/ Microsoft One drive/Dropbox etc.) frequently. | **BINT3** | |

*K.A. Asraar Ahmed is currently working as an Assistant Professor Senior Grade-1 at the VIT-AP University, VIT-AP School of Business, Amaravati Campus, Andhra Pradesh, India. He has more than 9 years of academic and research experience. He pursued his Doctor of Philosophy from Vellore Institute of Technology University Business School (VITBS), VIT University, Vellore, India. His area of expertise in Business Analytics using R/Excel/SPSS, Data Visualisation using Tableau, Data Science using R, Quantitative Research, Business Research Methods, Marketing research & Analytics, R statistics, and Statistical Package for Social Science (SPSS), and Production and Operations management.*

*Anoop Kumar Sahu is faculty in the Department of Industrial and Production Engineering at School of Studies in Engineering and Technology at Guru Ghasidas Vishwavidyalaya (A Central University), Bilaspur, Chhattisgarh.*

*Atul Kumar Sahu is faculty in the Department of Industrial and Production Engineering at School of Studies in Engineering and Technology at Guru Ghasidas Vishwavidyalaya (A Central University), Bilaspur, Chhattisgarh.*

*Nitin Kumar Sahu is faculty in the Department of Industrial and Production Engineering at School of Studies in Engineering and Technology at Guru Ghasidas Vishwavidyalaya (A Central University), Bilaspur, Chhattisgarh.*