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A Study on Intention to Adopt Digital Payment Systems in India: Impact of COVID-19 Pandemic

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A B S T R A C T

Digitalization and digital transformations have metamorphized the face of Financial Inclusion globally, more so, in cash obsessed economies like India. The purpose of our study is to empirically analyze the users' intention to adopt digital payment systems, post Demonetisation, during the COVID-19 pandemic in India. The conceptual framework for the study is based on the Unified Theory of Acceptance and Use of Technology (UTAUT) adoption model with added operationalized constructs of Perceived Risk and Stickiness to use Cash. A total of 326 respondents were surveyed using a pre-tested questionnaire during the Nationwide Lockdown 3.0 in India. These responses were analyzed using Partial Least Squares – Structural Equation Modelling (PLS-SEM) technique. The findings of the study revealed that performance expectancy and facilitating conditions directly influence the intention of individuals to use digital payment systems, whereas the effect of perceived ease of use on digital payment systems is mediated through the attitude towards the digital payment systems during COVID-19 pandemic situation. Implications of the proposed adoption model are discussed. This will enable the other developing economies to formulate a digital ecosystem, that is here to stay even after the pandemic.[1)]

Keywords: Digital Payment Systems, Digitalization, COVID-19 Pandemic, UTAUT, Perceived Risk, Stickiness towards Cash

Ⅰ. Introduction

Payments are the connective tissues of the financial ecosystem in every economy. Digitalization, Fintech Revolution and the digital transformations have brought about sea change in the payment scenario across economies of the world. These technologies also impacted the process of banking and financial institutions (Alalwan et al., 2017; Lou et al., 2010). The continuous evolution and convergence of technologies helped the financial institutions to introduce new services at regular intervals like core banking solutions, check clearance systems, and digital payments (Guraău, 2002).

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In India, digital innovations and technologies for Banking and Financial sector is entrusted with the Reserve Bank of India, central banker and Financial Inclusion, Financial Literacy and ICT collaborator. The Reserve Bank's Payment and Settlement Systems Vision 2019-21 document's overarching goal is to ensure deepening of digital payment platforms offering e-payment options that are safe, secure, convenient, quick and affordable. The four pillars instrumental for achieving the same are encouraging healthy competition, ensuring affordable costs (setting up Payments Infrastructure Development Fund), customer centricity with increased confidence and improved convenience.[2] This vision is in consensus with the global UN's sustainable goal of Financial Inclusion of the unserved and underserved population by 2020. Since 2007-08, all economies are endeavouring towards financial inclusion. Digitalization and digital transformations have acted as catalyst in achieving inclusion of the masses, globally and in cash dominant economy of India, also evident from the success of the JAM - Trinity Amalgam of Prime Minister's Jan Dhan Yojana, Aadhar Identification number and Mobile Banking. However, prior to Demonetisation of November 2016, Indian economy was more cash obsessed and the payments divide between cash vs. digital payments inevitably existed. (Ilankumaran, 2019) However, post Demonetisation and driven by the central banker's progressive regulatory policies, the payment system indicators in India have witnessed transformation, which is evidenced herewith in the graphical representations – <Chart 1>: Payment System Indicators – Total Digital Payments in India from 2017-18 to 2019-20 and <Chart 2>: Payment System Indicators – Paper based Instruments; Annual Turnover – April to March from 2017-18 to 2019-20.

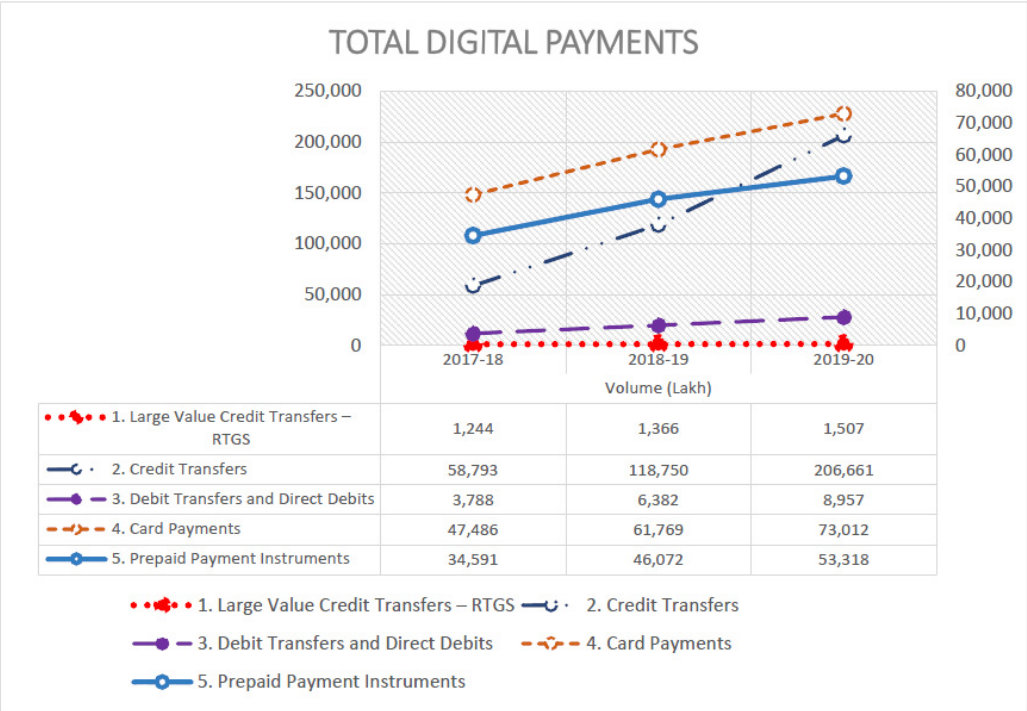
However, the Reserve Bank of India's Annual Report[3] revealed that the COVID-19 Pandemic had brought about decline in digital transactions during the period of January-May 2020 by approximately 25.5 per cent (y-o-y). On the contrary, the currency with the public accelerated by 11.2 per cent on February 28, 2020 to 21.3 per cent on June 19, 2020. The attenuation in the digital transactions during the COVID-19 Pandemic lockdown had been reported as indicative of the integration of cash – obsessed (dominant) Indian economy vis-à-vis digital Indian economy[4]. Our research motivation is to analyze the underlying factors impacting the intention of users to adopt and use Digital Payment Systems, which had *prima facie*, accelerated post Demonetisation (Refer <Chart 1>) in contrast to Cash/ Paper based Instruments (Refer <Chart 2>). The Impact of COVID-19 Pandemic on the adoption and usage of Digital Payment Systems is necessitated from the argument that users' behavioral intention and attitude is different during normal conditions vis-à-vis emergency situations, be it a financial emergency (Demonetisation) or a medical emergency (COVID-19 Pandemic) especially, Stickiness to use Cash as payment system vis-à-vis Digital Payment Systems in Indian context. Priorities of citizens become changed and they focus on the protection of the life of their kin. Further, these situations also impact the transactions of financial services in multiple ways, for example, change in priorities of people,

1) Digital payments: Pandemic does what demonetization coul dn't do" Economic Times dated October 01, 2020. Ravindra Pandey, Chief Digital Officer, State Bank of India.

2) https://m.rbi.org.in//scripts/AnnualReportPublications.aspx?Id=1293. Reserve Bank Annual Report dated August 25,2020.

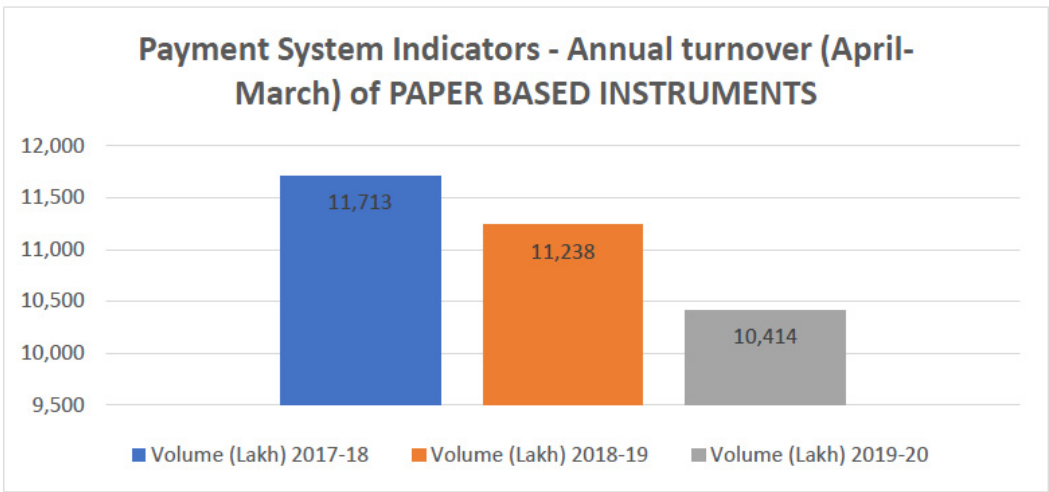
3) https://m.rbi.org.in//scripts/AnnualReportPublications.aspx?Id=1293. Reserve Bank Annual Report dated August 25,2020.

4) https://m.rbi.org.in//scripts/AnnualReportPublications.aspx?Id=1293. Reserve Bank Annual Report dated August 25,2020.



Source: Reserve Bank Annual Report dated August 25, 2020.

<Chart 1> Payment System Indicators: Total Digital Payments in India
(Annual Turnover - April to March; Volume in lakh)



Source: Reserve Bank Annual Report dated August 25, 2020.

<Chart 2> Payment System Indicators -Annual Turnover (April - March) of Paper Based Instruments

a complete shutdown of the cities, and regulatory bodies or agencies' guidelines to avoid infection (CDC, 2020). Also, World Health Organization requested to sanitize hands after handling cash (Jagannathan, 2020) and Indian Bank Association asked to refrain from visiting banks and use online banking facilities from home (Chakrabarty, 2020). Hence, digital payment systems become more important for citizens to perform their basic activities without risking their lives during a crisis like COVID-19 Pandemic. However, to what extent are the Digital Payment Systems, as new technologies, accepted and adopted by citizens in the Indian sub-continent? Moreover, the impact of the COVID-19 Pandemic on the adoption and acceptance of Digital payment systems (DPS) are the research questions. The research deals with this gap by empirically investigating, validating and drawing from the Technology Acceptance Model and Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al., 2003). Specific constructs are used to empirically analyze, evaluate and develop a conceptual framework to interpret the intention and attitude of users towards adoption of Digital Payment Systems vs. Cash, with special reference to COVID-19 Pandemic situation.

The remainder of this paper is organized as follows: the next section presents the literature review on digital payment systems, the UTAUT model, and other models. Then, the next section presents the conceptual model and hypotheses of the study, followed by the research methodology. The results and implications of the study are discussed. The limitations of the study and concluding remarks are discussed in the final section of the paper.

Ⅱ. Literature Review and Theoretical Background

This section provides an overview of digital payment systems and the model used in the study to examine the factors which influence the adoption of payment systems during crises.

2.1. Digital Payments in India: An Overview

Digital platforms and digital payments provide multiple benefits of speed, security, transparency, cost efficiency, scalability, removal of geographical and physical barriers and in promoting women's economic empowerment by facilitating greater account ownership and asset accumulation (Klapper and Singer, 2014). Coupled with the benefits mentioned, digital payments have enabled to cut corruption and increased accessibility in rural areas for emerging economies like India (Singh, 2018).

As part of Digital India initiative was launched 'India Stack', an inclusive digital technology ecosystem for presence less, paperless and cashless service delivery. The Ministry of Electronics & Information Technology (MeitY), along with Centre for Digital Financial Inclusion (CDFI) have notified 'Guidelines for Electronic Payments and receipts (EPR)'; and, are endeavouring all the Central/State Government departments/ministries to shift from cash/paper-based payments and receipts transactions to 'electronic or digital modes' only[5].

Thanks to the ubiquity and efficacy of digital payment systems: National Automated Clearing House (NACH) and Aadhar Enabled Payment System (AePS) of National Payments Corporation of India (NPCI), India had saved US $2 billion (INR 131

5) http://www.cdfi.in/our-works/epr

billion rupees) in its LPG fuel subsidy program, which is the world's largest social cash transfer programme, by paying cooking gas consumers directly into their bank accounts. When Indian government officials made social security pension payments through digital smart cards instead of manual cash payments at grass- root levels (rural areas), there was 47% reduction in bribe demands[6].

The Reserve Bank of India has been instrumental in propelling the Digital Payment Systems by taking host of measures[7] like Online Dispute Resolution (ODR) - a self-regulatory organization, Survey for Digital Payment Awareness Pan India, Legal Entity Identifier (LEI), Construction and Publication of Composite Digital Payments Index (DPI), 24×7 NEFT (National Electronic Funds Transfer).

2.2. Digital Payment System - Definition

The United Nations Capital Development Fund had set up an alliance comprising of 75 member nations, 'The Better Than Cash Alliance' committed to accelerate transition from cash to digital payments globally through excellence in advocacy, knowledge, efficiency, transparency[8].

The Better Than Cash Alliance has not defined Digital Payments in precise terms, but has drawn categorical inferences from two dimensions:

- the underlying nature of the payment instrument
  - if the payment instrument is paper based requiring authorization, it is non-digital, otherwise it is 'Digital'; or
  - if the instrument used for transfer is non-cash, then it is 'Digital'
- the payer-payee interface
  - if both the payer and payee use electronic means to pay and receive payments, it is 'Digital'; or
  - at least one of the parties uses electronic and non-cash transfer for either payment or receipt, then it is 'Digital'.

The Reserve Bank of India's working definition of Digital Payment Systems encompasses the following payment systems[9]: (Please Refer <Chart 1>)

- Large Value Credit Transfers – Real Time Gross Settlements (RTGS)
- Retail Segment Credit Transfers comprising of Aadhar Enabled Payment Systems (AePS); Aadhar Payment Bridge System (APBS); Electronic Clearing System Credit (ECS Cr); Immediate Payment Service (IMPS); National Automated Clearing House Credit (NACH Cr); National Electronic Funds Transfer (NEFT); Unified Payments Interface (UPI),
- Debit Transfers and Direct Debits comprising of Bharat Interface for Money (BHIM) Aadhar Pay; Electronic Clearing System Debit (ECS Dr.); National Automated Clearing House Debit (NACH Dr.); National Electronic Toll Collection (NETC- Linked to bank Accounts),
- Card Payments comprising of Credit Cards, Debit Cards, Near Field Communication (NFC) Cards,
- Prepaid Payment Instruments.

6) https://www.betterthancash.org/why-digital-payments
7) https://www.rbi.org.in/Scripts/AnnualReportPublications.aspx?Id=1298
8) https://www.betterthancash.org/
9) https://m.rbi.org.in//scripts/AnnualReportPublications.aspx?Id=1293. Reserve Bank Annual Report dated August 25, 2020.

2.3. Unified Theory of Acceptance and Use of Technology (UTAUT)

Information Systems Research deals with understanding the factors influencing adoption of new and innovative information technologies by users, users behavioral and psychological motivators explaining their acceptance and use of the technology.

Lee (2016) have discussed the paradigm shift in researches from development, adoption and application of Information Systems to Fintech and other innovative technological systems. Digital Payment Systems are an innovative technological disruption payments and receipts medium for carrying out transactions by users across the globe. The review of literature revealed that no studies using the UTAUT model to understand intention and attitude of users towards Digital Payment Systems adoption was done in Indian context. Studies on mobile banking adoption have been carried out though on Indian users (Singh and Shrivastava, 2018). The present study envisages to understand the factors influencing the intention and attitude of users to adopt and use Digital Payment Systems for their transactions, especially during COVID-19 Pandemic (where the need to use Digital Payment Systems was sort of mandated by circumstances). For the study, therefore, the competing UTAUT model with the original four constructs is used as base model, augmented with two contextual factors, namely, Perceived Risk and Stickiness to use Cash.

UTAUT model was proposed by Venkatesh et al. (2003) to understand the adoption of technology, which is considered as an extension to TAM (Pikkarainen et al., 2004). UTAUT model was developed on the following eight theories: Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), combined TAM and TPB model, the Motivational Model (MM), Innovation Diffusion Theory (IDT), the PC Utilization Model (PCUM), and the Social Cognitive Theory (SCT).

According to the UTAUT model, four factors influence the adoption and usage of technology by users, which are: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). The UTAUT model not only emphasizes the core determinants that influence the intention to use and actual usage of technology but also provides flexibility to research scholars to extend the model by adding factors or moderating variables as per the requirement of the study. For example, the trust construct was added in this model to include the uncertainty in transactions created due to the external environment (Alalwan et al., 2016) and perceived risk construct augmented to this model while studying the usage pattern among the users of different nations (Merhi et al., 2019; Zhou, 2012).

2.4. Related studies

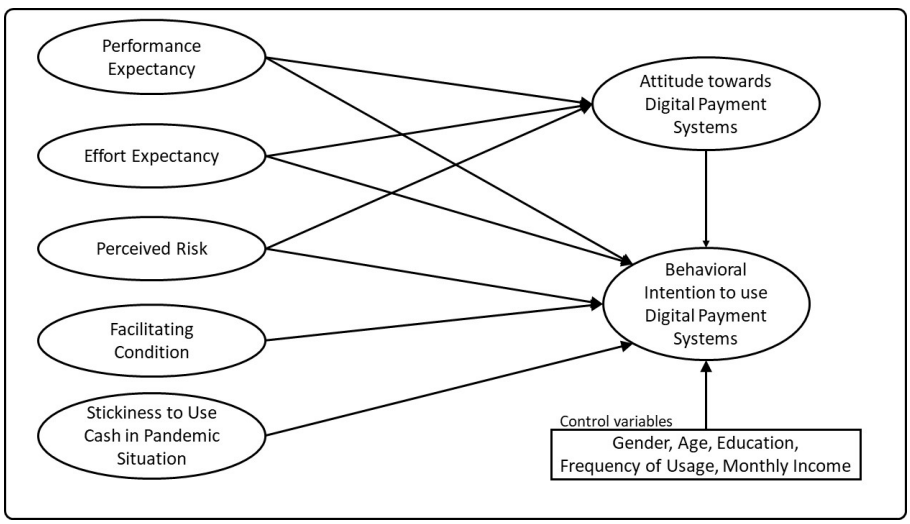
Other models are also used to explain the adoption and usage of new technology. Among, these the Technology Acceptance Model has been widely used to explain the factors behind the acceptance of the technology. Further, during the study of attitudinal and behavioral factors of individuals on technology acceptance, Tan and Teo (2000) proposed a framework on the adoption of internet banking based on the Theory of Planned Behavior and Diffusion of Innovation Theory. Another set of studies examined the perceived risk as a critical factor to adopt technology. A trust-based model proposed by Kim et al. (2008) was used to study factors of acceptance of mobile banking by the consumers (Lou et al., 2010). The Information System success model pro-

posed by DeLone and McLean (2004) also used to examine the indirect effect of information quality and service quality on the adoption of mobile payment systems (Sharma et al., 2019; Zhou, 2012).

Ⅲ. Research Model and Hypotheses Development

This study is developed on the UTAUT model and extended by two contextual factors to examine the behavioral intention of consumers to adopt the digital payment systems, especially, during the COVID-19 pandemic. This study used the core constructs of the UTAUT model, except, for the Social influence factor. This study was conducted during COVID-19 pandemic scenario, where citizens were following the guidelines issued by various institutions and agencies like the World Health Organization, and the Central/State Governments. Citizens were taking precautionary steps to protect themselves and their kin. Similarly, the same behavior depicted by all the member of the society. Hence, the social/professional/societal image did not influence the user's preference towards the usage of digital payment systems. Hence, this construct was dropped from the study.

This study also analyzed the two additional contextual factors, viz., Perceived risk and Stickiness to use the cash, especially, during the COVID-19 Pandemic. The high uncertainty associated with the financial services, by which the digital payment systems could be considered as highly risky products (Lou et al., 2010). Another factor, the stickiness to use cash is also considered for this study. Though the transaction value through digital payment systems has been growing at high-speed, still cash is dominated over other digital payment modes in India, being cash obsessed (Ilankumaran, 2019). Indians are more comfortable with the cash payment system, and this system is more prevalent in the rural and semi-urban areas which comprise more than three-fourth of the Indian population (Dudharejia, 2018). Therefore, this study included perceived risk and stickiness to use cash as augmentation to the UTAUT model. Further, the conceptual model of



<Figure 1> Research Model

this study included a few control variables in order to accurately measure the influence of factors on the acceptance of digital payment systems. The list of control variables used in this study is gender, age, educational qualification, frequency of usage of payment systems, and monthly income. <Figure 1> presents the proposed research model of the study.

3.1. Performance expectancy (PE)

Performance expectancy (PE) is defined "as the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003, p. 447). In other words, PE can be defined as the degree to which a user believes that usage of digital payment systems will provide additional benefits during his/her completion of a task. Prior works established that the direct impact of PE on attitude (Bailey et al., 2017; Rana et al., 2017; Taylor and Todd, 1995). A positive attitude of users towards digital payment systems if they perceived some benefits by using it. The direct benefits of Digital payment systems (DPS) positively influence the attitude of users. Further, previous works also found a positive relationship between performance expectancy and intention to use technologies (Chin and Beasley, 2019; Lou et al., 2010; Merhi et al., 2019; Zhou, 2012). Digital payment systems (DPS) enable users to do transactions from anyplace at any time. This flexibility increases the performance of users (Alalwan et al., 2017). During COVID-19, performance features of DPS will motivate the users to perform the transaction. Therefore, this study proposes that:

H1: Performance expectancy (PE) positively influences the attitude of users towards digital payment systems.

H2: Performance expectancy (PE) positively influences the behavioral intention of users towards digital payment systems.

3.2. Effort expectancy (EE)

Effort expectancy (EE) is defined "as the degree of ease associated with the use of the system" (Venkatesh et al., 2003, p. 450). In this paper, Effort Expectancy refers to the users' perception of the required effort for using Digital Payment Systems (DPS). Prior work established that EE is an important factor for driving attitude (Bailey et al., 2017; Rana et al., 2017; Taylor and Todd, 1995). EE shows the difficulty of using various DPS. Due to continuous evolution in technology and the different mechanism to use digital platform systems creates challenges to the users. Therefore, users require skills and awareness about the usage of DPS. If users find DPS difficult to use then they may be reluctant to use DPS. Previous studies (Alalwan et al., 2017; Lou et al., 2010; Merhi et al., 2019; Zhou, 2012) have validated the role of EE in the adoption of technology. Therefore, this study proposes that:

H3: Effort Expectancy (EE) positively influences the attitude of users towards digital payment systems.

H4: Effort Expectancy (EE) positively influences the behavioral intention of users towards digital payment systems.

3.3. Perceived risk (PR)

Perceived risk (PR) is defined as 'the potential for loss in the pursuit of a desired outcome of using an e-service' (Featherman and Pavlou, 2003). The online transfer of funds using different payment methods are perceived as convenient but risky

activities. Previous studies established that perceived risk influences users' decisions (Harris et al., 2010; Liébana-Cabanillas et al., 2018; Zhou, 2012) to carry out online financial transactions involving cash. Here, in our study, Perceived risk of performing online transactions of payments and receipts adopting Digital Payment Systems (new technology) are vulnerable to security risk, financial risk, privacy risk as compared to the traditional medium of using cash for transactions. Studies by Featherman and Pavlou (2003), Brown et al. (2003), Laukkanen and Lauronen (2005), Kuisma et al. (2007), Laukkanen et al. (2007b), Laukkanen and Kiviniemi, 2010; Thakur and Srivastava (2014), Slade et al. (2015) have all emphasized the role of security concerns in internet banking/mobile banking/remote mobile payment transactions, like loss of OTP/PIN, wrong tapping of bill, wrong input and so on. Perceived risk is, therefore, an important determinant to the adoption of technologies, especially when money is involved in the usage (Harris et al., 2010). Hence, this study proposes that:

H5: Perceived risk (PR) negatively influences the attitude of users towards digital payment systems.

H6: Perceived risk (PR) negatively influences the behavioral intention of users towards digital payment systems.

3.4. Facilitating conditions (FC)

Facilitating conditions (FC) are defined "as the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh et al., 2003, p. 453). It indicates the users' ability and required resources to use digital payment systems. Users require a certain level of knowledge and skill to operate DPS. FC also refers to the availability, accessibility, and scalability of digital payment systems to support the instant transfer of funds. Further, the availability of trained support staff to resolve the transaction issues and guide the users to use DPS. Prior works established the impact of facilitating conditions on the behavioral intention to use technology (Alalwan et al., 2017; Zhou, 2012). Therefore, this study proposes that:

H7: Facilitating conditions (FC) positively influences the behavioral intention of users to use digital payment systems.

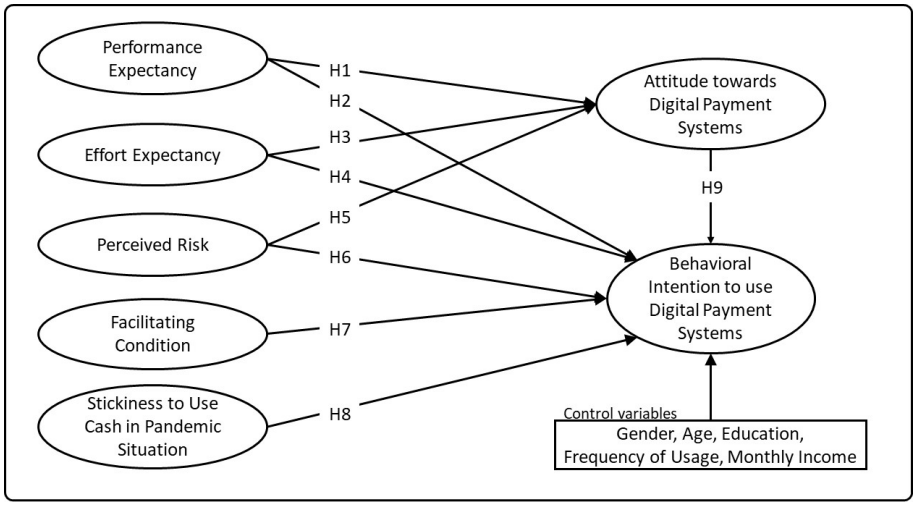
3.5. Stickiness to use Cash (ST)

Stickiness is defined as "the degree of users' willingness to return to and prolong their duration of each stay in a social network site (SNS)" (Yeh et al., 2013, p. 39). In this study, stickiness to use cash could be conceptualized as the usage and re-use of cash in transactions for the prolonged duration, even during the COVID-19 pandemic. In other words, the preference for using cash as a payment method instead of digital payment systems for prolonged duration, despite mandated guidelines and promotion of Digital Payment Systems by Reserve Bank of India. Cash payments usually require both parties (payer and payee) to be present to perform a transaction without involving any third-parties. Thus, cash makes the transaction very simple. Therefore, this study proposes that:

H8: Stickiness to use cash (ST) negatively influences the behavioral intention of users to use digital payment systems.

3.6. Attitude (ATT)

Attitude toward using technology is defined as "an individual's overall affective reaction to using



<Figure 2> Research Model with Hypotheses

a system" (Venkatesh et al., 2003, p. 455). Prior studies have established a mediating role of attitude between intention to use technology and other constructs (Chiu et al., 2005; Liang et al., 2013; Taylor and Todd, 1995). With respect to this study, Attitude, is acting as a mediator between intention to use Digital Payment Systems and the three constructs, namely, performance expectancy, effort expectancy, and perceived risk. Further, attitude also exerts a direct influence on the intention to use technology (Chiu et al., 2005; Liang et al., 2013). Thereby, this study proposes that,

H9: Attitude (ST) positively influences the behavioral intention of users to use digital payment systems.

3.6.1. Control variables

Demographic variables like Gender, Age, Education, Income, and Usage Frequency are control variables, which are shown in the conceptual model of our study as shown in <Figure 2>.

Ⅳ. Research Methodology

4.1. Sample selection and Data Collection Procedure

To collect the data on the intention to use digital payment systems by the customers, especially during medical emergency, COVID-19 Pandemic, an online survey was conducted during the nationwide lockdown 3.0[10] imposed under the Disaster Management Act, 2005, from May 04, 2020, to May 19, 2020.

PLS path modelling technique gives the benefit of not being affected by small sample size. For ascertaining the adequate sample size for the study, the thumb rule of ten times the number of items of the biggest construct in research model was used (Gefen, 2000). Hence, the required sample size was 240 respondents. The nationwide lockdown necessitated that the primary data collection through questionnaire be carried out in online mode only.

10) Lockdown due to COVID-19 pandemic. Website: https://economictimes.indiatimes.com/news/politics-and-nation/govt-extends-lockdown-by-two-weeks-permits-considerable-relaxations-in-green-and-orange-zones/articleshow/75491935.cms

Resultingly, the survey was carried on through Google forms using convenience sampling and snowball sampling, Pan India. The rationale behind using convenience sampling and snowball sampling was to have a fair representative sample, barring geographical constraints and including citizens from rural, semi-urban, urban and metropolitan areas of India, through social networking platforms. An email with a survey link was sent to participants and then, they spread the survey link among their network. A total of 326 responses were analyzed in this study. Respondents were requested to provide demographic information along with the survey responses. Since all the questions were marked mandatory using '*' sign, the problem of non-response bias does not affect the study.

The descriptive data collected for this research revealed that the sample contains a slightly higher percentage of male respondents (59 percent) compared to female respondents (41 percent). The majority of respondents belonged to two age-groups, first, between 21 and 35 years (42 percent) and another, between 36 and 50 years (41 percent), whereas only 17 percent of users were scattered in the rest of the age-groups (refer <Table 1>). This type of sample distribution reflects that a big share of the working-age population had knowledge about digital payment systems and used it in their daily lives. Regarding the educational level of the respondents, 5 percent of the sample have a diploma and only 3 percent of the sample do not have any college degree. In short, 92 percent of the respondents have at least completed the undergraduate course. Approximately, more than 82 percent of the respondent were earning more than the average monthly income[11] of an Indian, whereas 70 percent of the respondents were earning more than INR 50,000 per month[12]. This sample includes respondents with a different frequency of usage of digital payment systems and three-fourth of the sample have used more than four digital payment systems. However, only 22 percent of the respondents are daily using any kind of digital payment systems.

The demographic features of the respondents are presented in <Table 1>.

4.2. Instrument design

This empirical study has used the constructs well defined in previous studies regarding acceptance and use of technology, with extensions and modifications to incorporate the context of usage of Digital Payment Systems during the COVID-19 pandemic situation during the Nationwide Lockdown 3.0 imposed under the Disaster Management Act, 2005. The multi item constructs in the hypothesized framework were used to calculate the measurement properties in the final measurement model using Partial Least Squares-Structural Equation Modelling (PLS-SEM), (Hair et al., 2006). The reflective measurement model aptly suited the study because causality is from the latent constructs to their measures or indicators. The questionnaire included items to measure performance expectancy, effort expectancy, perceived risk, facilitating condition, stickiness to use cash, attitude, and intention to use. Respondents were requested to express using the five-point Likert-scale, ranging from "strongly disagree = 1" to "strongly agree = 5" for all the multi- item reflective constructs. The final measurement model used in the study are given in <Appendix A>.

11) The average monthly income of an Indian is INR 11,284. website: https://www.businesstoday.in/current/economy-politics/india-per-capita-income-rises-68-to-rs-11254-a-month-in-fy20/story/393333.html

12) $667 per month, at 1$ = INR 75 (approx.) Pls note 1$ = 73.99 INR on November 30, 2020.

<Table 1> Demographic Information of the Respondents

Variables	Category	Frequency	Percentage
Gender	Male	193	59%
	Female	133	41%
Age group	Below 20	8	2%
	21 - 35	137	42%
	36 - 50	135	41%
	51 - 65	42	13%
	Above 65	4	1%
Education	No College Degree	11	3%
	Diploma	15	5%
	Graduate degree	121	37%
	Post Graduate degree / Masters	151	46%
	Doctorate	28	9%
Monthly Income	Less than ₹ 20000	37	11%
	₹ 20000 - ₹ 50000	60	18%
	₹ 50000 - ₹ One Lac	105	32%
	Above ₹ One Lac	124	38%
Prior experience of using digital payment systems	Yes	310	95%
	No	16	5%
Frequency of usage of digital payment systems	Once in 2 to 3 days	97	30%
	Once in 4 to 6 days	76	23%
	Once or more than once in a day	73	22%
	Once in a week	54	17%
	Once in a month	26	8%
Number of payment systems used by a person	One (1)	13	4%
	Two (2)	11	3%
	Three (3)	21	6%
	Four (4)	24	7%
	Five (5)	18	6%
	Six (6)	41	13%
	Seven (7)	60	18%
	Eight (8)	37	11%
	Nine (9)	65	20%
	Ten (10)	36	11%
Number of payment systems used by a person	less than or equal to 5 payment systems	87	27%
	More than 5 payment systems	239	73%
Payment Modes	*99# USSD	42	An individual can use more than one payment system
	NEFT	256	
	RTGS	192	
	UPI	274	
	Mobile Banking	256	
	Mobile Wallets	257	
	Debit Card / Credit Card / NFC	311	
	IMPS	245	
	BHIM	192	
	NETC FASTag	151	

4.3. Statistical analysis

The data analysis was done in two stages. In the first stage, the fitness of the measurement model was tested. Cronbach's alpha and composite reliability were used to determine the reliability and internal consistency of the items used to measure the variables of this study. Further, convergent and discriminant validity tests were conducted to complete the fitness test of the measurement model. In the second stage, the Partial Least Squares-Structural Equation Modeling (PLS-SEM) technique was used to evaluate the hypothesized relationship between the latent variables of the proposed research model. The PLS-SEM path modelling technique is used in this study to test the conceptual research framework and assess the casual relationship between the indicators and latent constructs (Gudergan, 2008). PLS-SEM is preferred over Covariance Based -Structural Equation Modelling, because the former is a flexible technique to model the research constructs under study (Henseler, 2010) Firstly, the analysis is concerned with testing a theoretical framework from prediction perspective and distribution issues are a concern, due to lack of normality (Hair et al., 2019). Secondly, PLS-SEM proves valuable for analyzing secondary data from measurement theory perspective, since it permits unrestricted use of single item and formative measures (Hair, 2017a) in contrast to CB-SEM. Thirdly, when using PLS-SEM, researchers benefit from the method's high degree of statistical power as compared to CB-SEM, since, greater statistical power means that PLS-SEM is likely to identify relationships as significant when they are present in the population (Sarstedt, 2019). SmartPLS software (Ringle, 2015) was used to conduct the data analysis for this study.

Ⅴ. Data Analysis and Results

5.1. Measurement Model Analysis

PLS path models are primarily defined by two sets of linear equations, viz., the measurement model or outer model and the structural model or inner model. The measurement model describes the relationship between constructs and its observed indicators, whereas the structural model describes the relationship between constructs (Henseler, 2016). Reflective model was used to measure the operationalized constructs given in the <Appendix A> of the paper. The factor loading, reliability, and internal consistency of the operationalized constructs of the measurement model are presented in <Table 2>.

All items were loaded on separate factors with a factor loading greater than 0.9. To verify the reliability of the latent variables and internal consistency between the items, the values of Cronbach's alpha and Composite Reliability were calculated. These values for all constructs were greater than 0.8 which shows that the research model of this study is highly reliable and consistent (Nunnaly, 1978).

<Table 2> also shows the values of the average variance extracted (AVE) of the constructs. The AVE values of the constructs are above the 0.5 threshold, which confirms the convergent validity of the model (Fornell and Larcker, 1981). Further, the square root of the AVE of each construct was compared with the inter-construct correlation values (Fornell and Larcker, 1981; Hair et al., 2016).

For Discriminant validity, the Fornell-Larcker criterion (proposed by Fornell and Larcker, 1981) are shown in <Table 3> (bold values). Since, the outer loadings of an indicator of latent constructs are higher than all their cross loadings as compared to other constructs. This suggests that that the constructs are

<Table 2> Results of Factor Analysis, Internal Consistency Reliability (Cronbach Alpha > 0.7), Composite Reliability, Convergent Reliability (AVE > 0.5)

Construct	Factor loading	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Performance Expectancy (PE)	0.94, 0.95, 0.94	0.94	0.97	0.84
Effort expectancy (EE)	0.97, 0.97, 0.97	0.97	0.98	0.94
Perceived Risk (PR)	0.91, 0.92, 0.92, 0.92, 0.93, 0.92, 0.91	0.97	0.96	0.89
Facilitating Condition (FC)	0.94, 0.94, 0.83	0.89	0.93	0.82
Stickiness to use cash in Pandemic situation (ST)	0.96, 0.96, 0.95	0.95	0.97	0.91
Attitude towards Digital Payment Systems (ATT)	0.99, 0.99	0.97	0.98	0.97
Behavioral intention to use Digital Payment Systems (BI)	0.97, 0.97	0.94	0.97	0.95

<Table 3> Discriminant Validity of the Model

	PE	EE	PR	FC	ST	ATT	BI
Performance Expectancy (PE)	**0.95**						
Effort expectancy (EE)	0.93	**0.97**					
Perceived Risk (PR)	-0.41	-0.41	**0.92**				
Facilitating Condition (FC)	0.82	0.84	-0.42	**0.91**			
Stickiness to use cash in Pandemic situation (ST)	-0.51	-0.50	0.64	-0.52	**0.96**		
Attitude towards Digital Payment Systems (ATT)	0.72	0.72	-0.28	0.69	-0.42	**0.99**	
Behavioral intention to use Digital Payment Systems (BI)	0.84	0.82	-0.38	0.82	-0.51	0.74	**0.97**

factually different from each other constructs, by empirical standards.

5.2. Structural Model Analysis

After establishing the convergent and discriminant validity of the construct, the partial least squares (PLS) technique was used to methodically analyze the data on the SmartPLS tool. Hair et al. (2014) have suggested Structural Model key criteria for assessment are R^2 values, effect size (f^2), predictive relevance (Q^2). Associated Rules of Thumb for structural model assessment were employed to perform the analysis.

5.2.1. Collinearity Assessment

Henseler et al. (2016) have recommended that for assessing collinearity, tolerance values of each predictor construct, Variance Inflation Factor (VIF) should range between 0.20 and 5 (Ringle et al., 2015). However, Hair et al. (2017a) also recommend creation of higher order models, that can be supported by theory, if VIF values are above 5. VIF for outer elements (items) is given in <Table 4> and inner element

<Table 4> Collinearity Statistics of Outer Elements (Items)

Outer Elements (Items)	Variance Inflation Factor (VIF)
ATT_2	4.666
ATT_3	4.666
AU_1	3.424
AU_2	3.372
AU_3	2.189
BI_1	4.906
BI_3	4.906
EE_1	7.669
EE_2	9.257
EE_3	7.180
FC_1	4.552
FC_2	4.640
FC_3	1.882
FR_1	7.420
FR_2	7.963
PE_1	4.201
PE_2	4.430
PE_3	4.454
SI_1	8.543
SI_2	8.543
SR_1	7.281
SR_2	7.561
SR_3	5.304
SR_4	4.820
ST_1	5.198
ST_2	5.349
ST_3	5.181
TRU_1	1.727
TRU_3	9.238
TRU_4	8.718

<Table 5> Collinearity Statistics – VIF of ConstRucts (Inner Elements)

Constructs	ATT	BI_AU_	
ATT		2.287	Within Range
EE	7.598	8.979	
FC		3.755	Within Range
PE	7.567	8.069	
PR	1.212	1.745	Within Range
ST		1.998	Within Range

(constructs) is given in <Table 5> below:

Outer elements (items) with VIF > 5 especially, Social Influence SI_1, SI_2, Security Risk SR_2, Effort Expectancy EE_2, Financial Risk FR_1, FR_2, Trust TRU_3 and TRU_4, were eliminated from the final PLS path model.

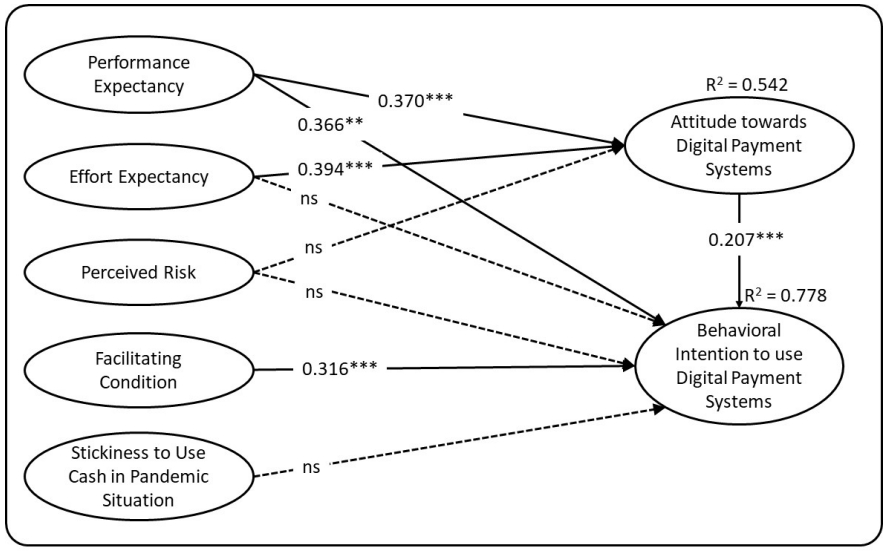
5.2.2. R^2 values

The next step in Structural Model assessment involves examining the R^2 value of the endogenous constructs. The R^2 is also referred to as in-sample predictive power (Rigdon, 2012) and ranges from 0 to 1, with higher values indicating a greater explanatory power. The conceptual research model explained a total of, approximately, 78% of the variance in the behavioral intention to use digital payment systems due to various antecedents, which are shown in <Figure 3>. This analysis also controlled the effect of demographic variables (age, gender, educational qualification, monthly income, and usage of digital payment systems) on the relationships.

5.2.3. Effect size: F-square (F^2) and Predictive Relevance (Q2)

Another means to assess the PLS path model's predictive accuracy is by calculating the Q^2 and effect size f^2 values. F^2 value provides an effect size index, that measures the effect of the population (sample) on all variables. F^2 results in <Table 6> shows exogenous constructs having large (> 0.35) effects on endogenous constructs. As a rule of thumb, values higher than 0.02, 0.15 and 0.35 depict small, medium and large F^2 effect sizes (Cohen, 1988).

Q-square statistic measures the predictive relevance of the model by reproducing the observed values by the model itself. As a Rule of Thumb,



*Note- ns: Not Significant, ***:p-value < 0.01; **:p-value < 0.05*

<Figure 3> The outcomes of PLS Modeling

<Table 6> F-square Values

F-Square values				
		Original Sample (O)	T Statistics (|O/STDEV|)	*P* Values
Attitude → Behavioral Intention	ATT → BI_&_AU	0.084	1.65	0.099
Effort Expectancy → Attitude	EE → ATT	0.045	1.442	0.149
Effort Expectancy → Behavioral Intention	EE → BI_&_AU	0.001	0.044	0.965
Facilitating Conditions → Behavioral Intention	FC → BI_&_AU	0.119	1.915	0.056
Performance Expectancy → Attitude	PE → ATT	0.039	1.133	0.257
Performance Expectancy → Behavioral Intention	PE → BI_&_AU	0.074	1.249	0.212
Perceived Risk → Attitude	PR → ATT	0.002	0.229	0.818
Perceived Risk → Behavioral Intention	PR → BI_&_AU	0	0.029	0.977
Stickiness to Use → Behavioral Intention	ST → BI_&_AU	0.007	0.467	0.64

Q^2 values higher than 0, 0.25, and 0.50 depict small, medium and large predictive relevance of the PLS -path model. This metric is based on blindfolding procedure and small differences between predicted and original values translate into higher Q^2 value. In our case, the construct cross-validated redundancy values are greater than 0.50 for the specific endogenous constructs, indicating higher predictive accuracy.

5.2.4. Bootstrapping

PLS path modeling tests of model fit rely on bootstrapping process to assess the significance of the path coefficients and determining the likelihood of

<Table 7> Q^2 Predictive Relevance Using Construct Cross-validated Redundancy

Construct Cross-validated Redundancy			
	SSO	SSE	Q^2 (= 1-SSE/SSO)
ATT	652	322.9267	0.504713607
BI_AU_	652	189.7805	0.708925631
EE	978	978	
FC	978	978	
PE	978	978	
PR	2282	2282	
ST	978	978	

obtaining discrepancy between empirical and model implied correlation matrix (Dijkstra and Henseler, 2015a). Moreover, since PLS-Sem is a non-parametric method, bootstrapping is used to determine statistical significance and Hair et al. (2017a) suggest BCa bootstrap confidence intervals for significance testing in case the bootstrap distribution of the indicator weights is skewed. For this study, following the Rule of Thumb procedure, 5000 samples were generated through the bootstrapping mechanism, and aggressively, tested the hypotheses. <Figure 3> depicts the outcomes of PLS modeling.

The outcomes of PLS modeling show that Performance Expectancy (PE) is positively influencing Attitude (ATT) towards digital payment systems and Behavioral Intention to use digital payment systems during COVID-19 Pandemic. Hypothesis 1 and 2 are supported. Effort Expectancy (EE) positively influences Attitude (ATT) of citizens towards digital payment systems during COVID-19 Pandemic. Hypothesis 3 is supported. However, the influence of Effort Expectancy on Behavioral Intention to use digital payment systems during the Pandemic is not statistically significant, thus hypothesis 4 is not supported. The influence of Perceived Risk on Attitude and Behavioral Intention to use digital payment systems is not statistically significant and hence, hypotheses 5 and 6 are not supported. Facilitating Conditions positively influences the Behavioral Intention of the citizens to use digital payment systems during the COVID-19 Pandemic, as evidenced by the statistically significant results. Hence, Hypothesis 7 is supported. Hypothesis 8, relating to Stickiness to Use Cash in Pandemic situations by citizens' is also not statistically significant. The latent construct of Attitude towards digital payment systems also positively influences behavioral intention to use, thus supporting hypothesis 9 of the study. Mediation analysis of the same is discussed in paragraph 5.2.5. Only, monthly income had a positive impact on individuals' intention to use digital payment systems whereas other control variables like Age, Gender and Educational background, were found to be insignificant as shown in <Table 8>.

5.2.5. Mediation Analysis

A construct's total effect is defined as the sum of direct and all indirect effects. The direct effects of structural model assessment with path coefficients (absolute size and sign) with significance (T statistic and P values at confidence intervals) have been discussed in <Table 8>. For indirect effects, mediation analysis is depicted in <Table 9>.

<Table 8> Path Coefficients with Control Variables

Path Coefficients with Control variables	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV	T Statistics (|O/STDEV|	*P* Values	
ATT → BI_&_AU	0.197	0.198	0.057	3.440	0.001	Significant
Age → BI_&_AU	-0.033	-0.033	0.032	1.059	0.290	Not Significant
EE → ATT	0.394	0.392	0.124	3.166	0.002	Significant
EE → BI_&_AU	0.074	0.068	0.150	0.490	0.624	Not Significant
FC → BI_&_AU	0.296	0.298	0.086	3.441	0.001	Significant
PE → ATT	0.370	0.367	0.139	2.663	0.008	Significant
PE → BI_&_AU	0.335	0.336	0.145	2.306	0.021	Significant
PR → ATT	0.036	0.031	0.054	0.670	0.503	Not Significant
PR → BI_&_AU	0.041	0.036	0.040	1.030	0.303	Not Significant
ST → BI_&_AU	-0.059	-0.058	0.050	1.178	0.239	Not Significant
Monthly Income → BI_&_AU	0.100	0.098	0.037	2.705	0.007	Significant

<Table 9> Mediation Analysis of Indirect Effects

a. Special Indirect Effect

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	*P* Values	
EE → ATT → BI_&_AU	0.081	0.080	0.034	2.371	**0.018**	Significant
PE →ATT → BI_&_AU	0.076	0.077	0.041	1.871	**0.061**	Significant
PR → ATT → BI_&_AU	0.008	0.007	0.012	0.608	**0.543**	Not Significant

Ⅵ. Discussion and Implications

The aim of this paper to examine the factors affecting the intention and adoption of citizens to use digital payment systems, with special emphasis of usage during COVID-19 Pandemic. To the best of our knowledge, this study is one of the first attempts to empirically evaluate and analyze the behavioral intention of the users adopting digital payment systems, including the impact of COVID-19 Pandemic. From the results obtained after PLS-SEM analysis, research constructs PE, EE, FC and ATT have significant positive influence on Behavioral Intention to use Digital payment systems. Performance expectancy has significant influence on Attitude and behavioral intention to use digital payment systems, which is in consensus with the original UTAUT model of Venkatesh et al. (2003). Effort Expectancy does not have a direct effect on the intention to use digital payment systems, but indirectly influencing by generating a positive attitude towards digital payment systems. Further, the radical changes in the transaction environment such as 24*7 availability of systems, quick resolution of issues, reliable and secure transmission medium attract the users to adopt the digital payment systems to accomplish basic activities of their life. However, during the crises, the severity of the risk of using digital payment systems is very

low than that of the risk of life. As survival becomes the priority of citizens. So, the perceived risk associated with digital payments does not have any impact on the individuals' intention to use digital payment systems. However, the habit of regularly using cash for leading their basic life does not have any influence on the intention to use digital payment systems during a crisis like situation.

6.1. Theoretical Implications

The basic premise of this study is to examine the various factors that influence the individuals' intention to use digital payment systems during the pandemic. This study empirically validated the extended UTAUT model to understand the intention of citizens to use digital payment systems. Hence, the outcomes of the current study contributed to the technology adoption literature as it integrates the perceived risk and stickiness to use cash with the UTAUT model. Further, this study adds to the literature on digital payment systems by exploring the antecedents behind the usage during a crisis.

6.2. Practical Implications

Technology plays a pivotal role to smoothly perform our day-to-day activities, especially, during a crisis like COVID-19 pandemic where the movement of people is restricted and the use of paper-notes or coins is avoided as a precautionary measure. This research has overwhelming implications for both policy-makers and financial institutions. The policy-maker incorporates the outcome while formulating strategies that provide a favorable environment to perform the transaction. For example, settlement of online transactions after the business hours, reduction in services charges, etc. will motivate individuals and firms to opt for the digital payment systems. A speed, secured, and reliable digital platforms significantly influence the intention of the users. So, the performance of digital payment systems along with facilitating condition significantly influence the customers' intention to use these systems during a crisis. On the other hand, regulatory bodies should also update the code of conduct to reduce the ambiguity in the transactions. Also, financial institutions should focus on training the staff to resolve the customers' issues. However, ease of using digital platforms during an emergency does not exert any influence on the behavioral intention, because people have limited options to do transactions and digital payment systems are one of the best available options. The associated risks with digital payment systems are compensated with the performance features and sometimes overlooked during an emergency. Therefore, the outcomes of the study suggest that the policy-makers and International Financial Bodies engaged in promoting financial inclusion should focus on performance and facilitating conditions synchronizing with digital financial education, so that more masses are aware of the potential benefits of Digital Payment Systems in normal conditions, as well as, pandemic situations like COVID-19.

Ⅶ. Limitations and Future Research

This study has some limitations, which can be taken care of in future studies. Firstly, the responses are collected through convenience and snowball sampling methods. For future researches, more representative and scientifically proven sampling techniques could be employed. Secondly, the original UTAUT model has analyzed and evaluated the moderating impact of demographic variables like Gender,

Age, and Experience on the behavioral intention to use the technology whereas, in this study, the demographic variables that are Gender, Age, Educational Qualification, Monthly Income, and Frequency of usage of digital payment systems were considered as controlled variables. Last but not least, this study executed in the Indian context, future studies testing the same across the countries would help to form the generalizability of the results because the banking norm and impact of crises vary from one nation to another.

Ⅷ. Conclusion

The outcomes of the study help to understand the factors that impact the citizens' intention to adopt and use the Digital Payment Systems. The impact of nationwide lockdown, due to the COVID-19 pandemic crisis on the attitude and behavioral intention of citizens to adopt and use digital payment systems was empirically evaluated and the research model developed showed that facilitating condition, and performance expectancy significantly impact the individual's intention to use the digital payment systems whereas effort expectancy has an indirect effect on the behavioral intention. Further, the attitude of citizens towards digital payment systems increases the intention to use financial services in digital mode. However, the perceived risk and stickiness to use cash did not exert any influence on the intention to use the digital payment system during the COVID-19 pandemic. Overall, this study will help the G 20 countries and other International financial institutions engaged in empowering the masses through digital financial inclusion to formulate new strategies and promote a digital ecosystem facilitating more inclusiveness through digitalization and Fintech revolution.

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<Appendix A> The Survey Instrument

Performance Expectancy (PE) (Venkatesh et al., 2003)

- PE1: I would find Digital Payment Systems useful in my daily life.
- PE2: Using Digital Payment Systems would help me accomplish things more quickly.
- PE3: Using Digital Payment Systems might increase productivity.

Effort Expectancy (EE) (Venkatesh et al., 2003)

- EE 1: I would find Digital Payment Systems easy to use.
- EE 2: My interaction with Digital Payment Systems would be clear and understandable.
- EE 3: It would easy for me to become skillful at using Digital Payment Systems.

Facilitating Conditions (FC) (Venkatesh et al., 2003)

- FC 1: I have the resources necessary to use digital payment systems.
- FC 2: I have the knowledge necessary to use digital payment systems.
- FC 3: A specific person or group (customer support services) is available for assistance with digital payment system difficulties

Perceived Risk (PR) (Featherman and Pavlou, 2003)

- PR 1: I would be worried about the accuracy of the input information while using digital payment systems.
- PR 2: I would be anxious about loss of connection/transaction failure while using digital payment systems.
- PR 3: I would have insecurity of PIN/OTP while using digital payment systems for financial transactions.
- PR 4: I would be doubtful of wrongly tapping the bill information while using digital payment systems.
- PR 5: I would be worried about third party access to my account while using digital payment systems.
- PR 6: Using digital payment systems increase my chances of losing money during financial transactions.
- PR 7: Using digital payment systems subjects my checking account to financial risk

Stickiness to use Cash (ST) (Lin, 2007)

- ST 1: I would use the cash payment system for a longer time than digital payment systems even during COVID-19 Pandemic
- ST 2: I often use cash payment as I can even during COVID-19 Pandemic

- ST 3: I always use cash payment system when I am online even during COVID-19 Pandemic

Attitude (ATT) (Taylor and Todd, 1995)

- ATT 1: Using digital payment systems is a good idea during COVID-19 Pandemic
- ATT 2: Using digital payment systems is wise during COVID-19 Pandemic
- ATT 3: Using digital payment systems is beneficial during COVID-19 Pandemic

Behavioral Intention (BI) (Venkatesh et al., 2003)

- BI 1: I intend to use digital payment systems during COVID-19 Pandemic.
- BI 2: I predict I will use digital payment systems in my daily life during COVID-19 Pandemic.
- BI 3: I plan to use digital payment systems frequently during COVID-19 Pandemic

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