Influence of Mobile Apps on Household Saving-Spending Behaviour

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Abstract

The study has attempted to assess the influence of use of mobile apps on household saving-spending behaviour. Accessing a digital library, three research hypotheses have been framed, and for executing the study, an online survey has been conducted amongst 107 employees of two leading private banks. A pre-test has affirmed the reliability and validity of the questionnaire. Inferential statistics have indicated likely rejection of all the null hypotheses and concluded that multiple determinants and use of mobile apps have a significant influence on saving and spending behaviour. Policy implications indicated and limitations have been acknowledged.

Key words: *Household saving, household spending, mobile apps, online survey, inferential statistics.*

1. Introduction

Mobile applications (henceforth termed as 'apps') have been defined as the technology downloaded and used in smart phones, tablets and personal digital assistance for multiple behavioural and psychological interventions (Elias, Fogger & McGuinness, 2014). Apps, the application softwares containing contents in digital shape have been gaining momentum and proliferations globally (Olff, 2015). The use of mobile apps in the banking industry has been promoted globally: in India, the Reserve Bank of India encourages use of mobile banking apps for multiple benefits they offer like round-the-clock service, time saving, substantial decrease in infrastructure costs, ease in payments, money transfers and even to make people accustomed with digital transactions. It has been argued that transactions through mobile banking are more secured than internet banking. Mobile banking through the dedicated apps of the banks in urban India has exceeded transactions carried out via desktop, ATM outlets and even by branches. A number of features such as secured transactional capabilities, self-service blended with multiple product marketing features have shaped the mobile banking apps to become unique. Transition to cashless economy has speeded up after demonetisation, which has further accelerated after the government's fiscal incentives in different forms. Literature has indicated multiple facets of user-centric services such as entertainment and productivity which have been provided by service providers through mobile apps; new apps are also being developed in response to changing consumer needs and demands (Zhong et al., 2016). The customer environment, involvement and assessment have been acknowledged as complex and critical tasks for generating and disseminating market intelligence of uniqueness of products and services and even firms' unique selling propositions. Notwithstanding many apps, developers now have been confronting numerous challenges. Apps' developers have been

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effectively and efficiently assessing the needs and expectations of customers for developing user-centric mobile apps. Big data (a huge database beyond the periphery of softwares) store, manage and capture data generated through multiple information technologies and systems such as mobile apps (Chan et al., 2016) making it capable of providing valuable information about customers' behaviour and opinions. Moreover, big data has enabled apps' developers to develop apps without accessing customer specific information and have supported taking data-driven decisions (Chen, Li & Wang, 2015). The use of smart phones for accessing its multiple inherent advantages have been acknowledged; e.g., as a tool for parsimony and time saving, capable of longer duration use, instant transfer of real time data and even in research studies for gathering data from the remotest corners and higher response rates resulting in substantial dropout rates.

Literature reveals that trends based on mobile usage would significantly attract research attention in the near future (Walsh, 2014) as customers prefer mobile apps to desktops for varied purposes e.g., in hotel bookings, health care, green field marketing, higher education, sports and even for household needs (Gasdia & Hoffman, 2014; Singh & Ranjan, 2016; Watson & Duffield, 2016). It has been argued that mobile device apps have been integrated with business processes which is likely to minimize users' response time, thereby resulting in enhanced workforce efficiency (Basole, 2005). National cultures and imitation effects based on cultural dimensions have played a significant role in mobile adoption which, in turn, have yielded cost saving and resource pooling strategies for the customers (Lee, Trimi & Changsoo, 2013). Furthermore, few challenges in the use of mobile apps in sectors such as higher education [e.g., lack of bandwidth spectrum, security system, trained staff and funds crunch (Motorola, 2012)], in the health sector [poor quality (Marley & Farooq, 2015), lack of clear heuristics (Baumel & Muench, 2016) and a lack of social networking (Wang, An & Lu, 2014)] have been indicated. Use of smart phones in quantitative research has been restricted for specific purposes such as for gathering data on demographics, market research, monitoring human behaviour and interactions, time use and plotting feelings in relation to location and even for compiling observational data (Patel et al., 2013).

Household saving and spending studies have encompassed multiple facets. The literature on household food spending has included monthly food expenses, high-valued quality food and meat consumption, food expenditure elasticity and demand for specific food (Jensen, 2006; Huang & Gale, 2009). The associations between household budgetary allocations and demands for other major heads of expenditure such as textiles, grocery, personal care and healthcare, expenses for children, and education expenses have also been reported (Thomas & Garland, 2004; Kingdon, 2005). Related studies on saving have referred to it in several ways e.g., increase in the value of net assets and excess of incomes over consumption expenditures (Browning & Lusardi, 1996). Saving determinants such as demographics, desired yield, uncertainty, retirement corpus, bequest, inflation predictions, liquidity and risk have been documented (Claus & Thomas, 2001; Agarwalla et al., 2013; Lusardi & Mitchell, 2014). Turning to Indian literature, studies on household budget preparations, significance and motivators of saving for girl child's education and marriage, retirement saving, Prime Minister Jan Dhan Yojana (PMJDY), Pradhan Mantri Suraksha Bima Yojana (PMSBY), Pradhan Mantri Jeevan Jyoti Bima Yojana (PMJJBY), National Savings Certificate, fixed deposits, life insurance products and precautionary saving have so far been attempted (Mathivannan & Selvakumar, 2011; Deb, 2015; Deb, 2016; Deb & Sarma, 2016). Indian research on digital applications on personal finance includes ATM withdrawal restrictions, e-banking satisfaction, credit card services and perceptions, ease of use of debit cards in multiple payments, motivators of e-filing of returns by young professionals, consumers' adoption of mobile technology for grocery purchase, and customers' perceptions on and satisfaction with mobile transactions (Ojha, Sahu & Gupta, 2009; Shukla & Sharma, 2016; Singh & Sinha, 2016). Further, studies have revealed the negative impact of perceived risk of online shopping (Srivastava & Sharma, 2020), adoption of mobile banking apps by rural customers (Chakraborty, 2019), and technology readiness and users' perceptions about mobile wallets (Sinha & Singh, 2019). Review of existing literature reveals the absence of any study on the impact of using mobile apps on household saving and spending behaviour. The current study attempts to fill this literature gap based on statistical evidence which, in turn, would likely open a new vista of studies.

This research contributes to existing literature as enumerated; *first*, it has produced a ready reference about the impact of use of mobile apps on household saving and spending behaviour in the Indian context, which itself has opened a new vista of posterior research. *Second*, it has affirmed the multiple household saving and spending determinants mostly in tune with literature. Furthermore, significant behavioural changes in household saving and spending after the use of mobile apps have also been reported based on empirical evidence. *Finally*, it has shown how Indian households have been better off by improving lifestyles and using financial services by accessing multiple apps with ease, which has accelerated the growth engine of the Indian economy. As far as the generalizability of the findings is concerned, the apps' developers should emphasize on designing customer-specific apps while users should use these apps optimally for their saving-spending decisions. The decision for adding advanced features in the existing apps or in the introduction of new apps, and the potential challenges for implementing the same may be analysed in the light of the findings of this study.

The subsequent sections are as follows: hypotheses have been developed in Section 2, research methodologies have been explained in Section 3, results and discussion have been presented in Section 4, conclusion in Section 5, limitations of the study in Section 6, practical implications in Section 7 and finally, roadmap for future studies has been sketched in Section 8.

2. Hypotheses Development

2.1 Determinants of Household Saving and Spending

Literature reveals that there are multiple factors that impact household saving; they can be categorized under demographics and economic factors. *Demographics* such as gender, age, marital status, education levels, income levels, family and financial literacy have been found to have a positive influence (Browning & Lusardi, 1996; de Palma et al., 2011; Lusardi & Mitchell, 2014). In contrast, a few studies have indicated the opposite and/or insignificant influences (Kiran & Dhawan, 2015)]. *Economic factors* e.g., risks and returns, liquidity, tax incentives and inflation have been acknowledged (Roos & Schmidt, 2012; Agarwalla et al., 2013). Moving to household expenditure, family expenditures have been divided into food, clothing, healthcare, education, transportation, life insurance, entertainment and committed monthly instalments towards capital expenditure (Pinjari & Bhat, 2010). The household decisions for owning cars is influenced by presence of children; similarly, expenditure on luxuries depends on whether the family has a double income source and has any control on income between the spouses (Duflo, 2003; Bhat & Sen, 2006). Based on this, the hypotheses are:

H_1: Demographics have a significant influence on saving and spending behaviour.

H_2: Economic factors have a significant influence on saving and spending behaviour.

2.2 Mobile apps and Household Saving and Spending

Literature reveals that the average selling price of smart phones has substantially reduced (Neeraj, 2016). Mobile apps have been identified as being extensively used for e-commerce (Livemint, 2016). These apps are used to explore sellers' specifications, pricing, critical reviews of past customers, etc. (e Marketer, 2016 January). Shopping through mobile apps has been gaining momentum globally and studies have indicated its huge growth potential (Wang, Malthouse & Krishnamurthi, 2015). Recent literature on consumer behaviour and economics reveals firms' myriad attempts to increase interaction with customers (Lemon &Verhoef, 2016). Firms have established 'engagement initiatives' to achieve an emotional connection with customers (Kumar & Pansari, 2016) which is likely to increase non-purchase touch points (Gill, Sridhar & Grewal, 2017). Mobile apps have assisted consumers in their purchase decisions (Yang, 2010). New technologies such as mobile apps have gained acceptance among consumers (Davis, Bagozzi & Warshaw, 1989). Global research studies have confirmed customer satisfaction with mobile commerce e.g., grocery and retail purchases, financial services, healthcare, fashion and travel expenditures have achieved significant positive outcomes (Kim et al., 2016). Moreover, the determinants and associated perceived risks of users adopting mobile technology have also been studied in depth (Al-rahmi & Othman, 2013). Finally, research on the effectiveness of mobile apps has been validated with higher trust from app users, brand preferences, and likelihood of purchases (Xu et al., 2014). Based on these, it has been hypothesized that:

H_3: Use of mobile apps has a significant influence on saving and spending behaviour.

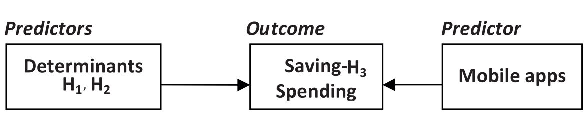

Figure 1: Conceptual model of the influence of mobile apps on saving and spending behaviour*

**Source: Author's research*

Figure 1 presents a conceptual model with the predictors likely to have a significant influence on the outcome. The study of the influence of mobile apps on household saving and spending behaviour has been carried out based on *ontology* (the existence of reality), *epistemology* (to gather knowledge, i.e., online survey to collect perceptions about the research problem), *methodology* (the overall approach), *axiology* (study objective) and has followed appropriate *methods* (data collection and analysis technique).

3. Methodology

The section has incorporated the following sub-sections.

3.1 Study Design

The author has adopted a cross-sectional study design and has conducted an online survey during July-October, 2018. The choice of study design is preferred for accessing few unique advantages such as ease in coding (Hayes & Baker, 2014).

3.2 Methods

3.2.1 Questionnaire Design

The author accessed digital libraries by using a few keywords. About 139 academic research papers published by global publishing houses were downloaded. A few expert opinions and study reports from commercial websites were reviewed. All this was used to frame 54 questions. Thereafter, a pilot study was run with 30 randomly chosen sample respondents for assessing the fitness, wording, order and writing style of the questionnaire (Zikmund & Babin, 2012). The responses were run through reliability test in SPSS-22. Based on Cronbach's alpha scores .5 and above, 46 questions were retained.

3.2.2 Sampling Design

The sample set was obtained from employees of India's two leading private banks. Email ids of employees were obtained from a reliable source. The questionnaire was mailed as a Google Doc file. The questionnaire was mailed to 375 employees in the first week of July, 2018 and by 31st October, 2018, 107 responses (28.53 percent) were received. This has been treated as the sample size. The 'ceiling' form of censoring strategy has been applied for dealing with missing data i.e. the deadline for considering responses. The rationale for choosing bank employees is that post-demonetisation and in an era of digital India, the banking sector has been widely using technology-based branchless banking services. There have been a number of mobile apps for multiple financial services such as mutual funds, online trading and conventional banking services being launched. Banks have been signing agreements with different commercial firms and service providers such as telecom companies, hospitality service providers and points of sale such as Big Bazaar, Spencer, etc. for extending lucrative offers to the apps users for retaining as well as attracting new customers. Further, it has been presumed that banking employees are comparatively more aware about the multiple benefits of using mobile apps for managing their household saving and spending. Limitations of funds and short timeline have confined the current study to the population of private bank employees. The sample size oscillated within the threshold limit of 30 and 500, which is a suitable range for social science studies (Roscoe, 1975). The sampling techniques have been designed as a combination of two non-probability techniques such as Convenience and Snowball as some sample respondents provided referrals of other prospective respondents' mail ids. Moreover, literature has indicated that people are reluctant to share their personal finance information (Renzetti & Lee, 1993), hence, following the Snowball technique was justified.

3.2.3 Data

3.2.3.1 Primary Data

The self-administered questionnaire has been designed in four sections. Section-I has a set of 13 questions to gather general information about the respondents' saving and spending habits. Section-II has 3 questions to assess the perceptions about the determinants of saving and spending behaviour. Sections III and IV have 15 questions each to assess the perceptions about saving and spending before and after using mobile apps. The entire questionnaire has been designed in Nominal scale.

3.2.3.2 Secondary Data

Primary sources explored include original academic research papers. Secondary sources include review papers and study reports by corporates. Tertiary sources include articles and reports accessed from Research Gate, Google Scholar, SSRN, etc.

3.2.4 Data Analysis Strategy

The study has applied Statistical Package for Social Science (SPSS) of IBM-version 22 for data analysis.

3.3 Variables

It has set two predictors–(1) *determinants of saving* and *(2) determinants of spending.* Determinants of saving have further been segregated into demographics (gender, age, family size, education levels and income levels) and economic factors (risk, returns, liquidity, tax incentives and inflation levels). Determinant of spending covers income levels. The other predictor has been set as *use of mobile apps* while the outcomes have been assumed as saving and spending behaviour. Furthermore, variables such as household joint behaviour, impacts of economic dimensions and culture on saving and spending behaviour and the like have been controlled.

3.4 Significance Level

For inferential statistical tests, significance level (α) as 5% has been assumed, i.e., in other words, the confidence level has been set at 95%.

3.5 Rationality of Statistical Tests

3.5.1 Cross Tabulations

Cross-Tabulation, a widely used statistical tool of social science has been used for analysing the nominal (categorical) data having two or more dimensional tables for recording frequencies in the cells of those tables (Reynolds, 1984). The co-occurrence of the mutually exclusive characteristics of each variable (i.e. high, medium and low) has been labelled by rows and columns. For example, in 2X2 contingency table, the sum total of rows have to correspond with the frequencies of the row variable and the probabilities of all the occurrences in those cells should be in agreement with the sum total of the table total. Researchers apply the tool for assessing whether the two variables have been independent or not and to judge the non-significant (no relationship) or significant (existence of relationship) relationship existing among the variables (Reitz & Dow, 1989).

3.5.2 Multiple Regressions

For assessing the influence of pre and post mobile apps on household saving and spending behaviour, multiple regressions have been run - a multivariate technique widely used by social scientists (Shakil, 2001) for determining the associations between two or more predictors and an outcome (McClave & Sincich, 2006). Even though the ANOVA (analysis of variance) represents the overall predictors' effects, the regression models have shown the ability for predicting the outcome (Pandis, 2015).

4. Results and Discussion

4.1 Descriptive Statistics

The sample statistics have been presented using mode. It has revealed that most of the participants are men (76.64 percent), their ages oscillated between 25-34 years (66.36 percent), graduates (57.01 percent), mostly with 3 members in their families (29.90 percent), earning per month at INR .03-.04 million (38.32 percent), monthly expenses in the range of INR .02-.03 million (54.21 percent), have been spending mostly on food (53.28 percent) and have been saving monthly INR .02-.03 million (53.28 percent). Moreover, 75.71 percent respondents have been assuming moderate risks in their savings with average returns (69.15 percent); having moderate liquidity preference (60.76 percent), tax preference (70.10 percent) and inflation estimation (65.42 percent).

4.2 Inferential Statistics

The numerical techniques applied for estimating the likely behaviour of the studied population based on statistical results on tests carried on the collected samples have been referred to as inferential statistics.

4.2.1 Cross Tabulations

For evaluating the impact of demographics and economic factors on household saving and spending behaviour (H_1 & H_2) Cross Tabulations were run and the results have been summarized in Tables 1, 2 & 3 respectively.

Table 1: Summary Results of Cross Tabulations of Demographics and Household Saving*

Variables		Results			
Demographics *(Predictors)*	**Household Savings *(Outcome)***	**Pearson's Chi-Square Value**	**Likelihood Ratio**	**Linear-by-Linear Asso.**	**Significance Value****
Gender	Household Saving	22.512	26.148	5.06	.001
Age	Household Saving	28.115	30.257	5.05	.002
Education Levels	Household Saving	30.750	33.478	5.12	.002
Income Levels	Household Saving	32.589	35.008	5.23	.001
Family Size	Household Saving	32.883	34.158	5.09	.000

**Primary data, **p<.05*

Table 2: Summary Results of Cross Tabulations of Economic Factors and Household Saving*

Variables		Results			
Economic Factors *(Predictors)*	**Household Saving*(Outcome)***	**Pearson's Chi-Square Value**	**Likelihood Ratio**	**Linear-by-Linear Asso.**	**Significance Value******
Risks	Household Saving	32.578	36.302	5.16	.004
Returns	Household Saving	31.518	35.759	5.04	.001
Liquidity Preference	Household Saving	34.145	37.238	5.41	.003
Tax Preference	Household Saving	35.759	37.192	5.44	.003
Inflation Estimations	Household Saving	28.583	34.573	5.09	.003

** Primary data, **p<.05*

Table 3: Summary Results of Cross Tabulations of Income Levels and Household Spending*

Variables		Results			
Income Levels *(Predictor)*	**Household Spending *(Outcome)***	**Pearson's Chi-Square Value**	**Likelihood Ratio**	**Linear-by-Linear Asso.**	**Significance Value******
Income Levels	Household Saving	36.121	39.227	5.13	.002

** Primary data, **p<.05*

In Tables 1, 2 & 3, the 1st columns present the Pearson Chi-square values indicating the null hypothesis of independence of row and column, which have also been supported by the corresponding lower significance values in the 4th columns and have provided evidence to reject the null hypothesis of 'no relationship'. The 2nd columns have shown the Likelihood ratios similar to the 1st columns and have validated the insignificant effect of smaller sample size, following the literature (Hays, 1963). The results of Linear-by-Linear Association tests have been presented in the 3rd columns which have run for checking the ordinal type data and have assumed equal and ordered intervals. Based on the Pearson correlation coefficient, an approximately chi-squared distribution on 1 d. f., for all the values have computed as significant (p<.05).The significant results affirm rejecting both H_{01} and H_{02} and the study has concluded that multiple determinants significantly influence household saving and spending behaviour.

4.2.3 Multiple Regressions

Multiple Regressions have been run to assess household saving and spending behaviour before and after using mobile apps. The results are presented in the following two tables.

Table 4: Model Summary*

Model	R	R^2	Adjusted R^2	Standard error of estimate	Change Statistics					Durbin-Watson
					R^2 Change	F Change	df_1	df_2	Sig. F Change	
1	.441	.406	.390	32.97	.335	93.44	1	105	.001	1.83
2	.711	.680	.845	41.68	.541	164.66	2	103	.000	

**Primary data*

Table 4 shows the model summary results where Model 1 deals with the predictor pre-mobile apps use and Model 2 with the predictor post mobile-apps use for the outcome household saving and spending behaviour. The first column R shows the simple correlation results between the predictors and the outcome which have been computed as .406 and .680 for the two models respectively. The following column R^2 values stood at .390 and .645 respectively which is interpreted as - the first predictor has been able to represent 39 percent of the outcome variable which has been raised to 84.5 percent by inclusion of the second variable i.e., in other words, a whopping 45.5 percent increase in saving and spending decisions during post mobile apps use. For both the models, the 3rd column (adjusted R^2) results have calculated values approximate to the second column (R^2), supporting the conclusion that the samples have likely been drawn from the study population which has affirmed good cross-validity of the models. In the Change Statistics section, R^2 value has reached .335 (Model 1) and .541 (Model 2) by simultaneous significant F-ratios ($p<.05$). Eventually, the Durbin-Watson test indicates a value close to 2 affirming the assumption of independent error.

Table 5: ANOVA Results*

Model		Sum of Squares (SS)	d. f.	Mean Square [SS/d. f.]	F	Sig.
Model 1	Regression	241587.10	1	241587.10	93.19	.002*
	Residual	841967.39	105	8018.73		
	Total	1083554.49	106			
Model 2	Regression	687219.22	2	343609.61	104.27	.000*
	Residual	715896.95	104	6883.62		
	Total	1403116.17	106			

Predictor: (Constant), Pre-Mobile apps use ** Primary data*
Predictors: (Constant), Post-Mobile apps use *Outcome: Saving and Spending behaviour*

The analysis of variance (ANOVA) results from Table 5 has indicated statistically significant improvements in the fitness of both of the models as evident from the F ratios which have reported an increasing trend from 93.19 to 104.27 ($p<.05$). The increasing trend has supported the likely nullification of H_{03} and inferring that post-mobile apps use, household saving and spending behaviour was probably significantly impacted, in conformity with global literature (Kim et al., 2016).

5. Conclusion

The study focuses on assessing the impact of use of multiple mobile apps on household saving and spending behaviour. Accessing digital library of a central university and other relevant e-resources, three research hypotheses and a conceptual model were developed for executing the study. Cross-tabulations have been applied to assess the impact of multiple determinants on household saving and spending behaviour and the significant results have supported the likely rejection of both H_{01} and H_{02}. For testing the third null hypothesis, Multiple regression analysis was used. The statistically significant results have affirmed the likely rejection of H_{03} and the corresponding research hypothesis was probably found to be true.

The current study is primarily confined to saving and spending behaviours using mobile apps, but in practice, mobile apps are being used in a wider spectrum addressing different facets of our lives. There is a common fallacy that mobile apps can only be used when one has internet connectivity, but in reality, once the apps have been downloaded and stored, these can be used even without internet connectivity. Indians are conservative when it comes to their personal finances. They believe in high involvement and thoughtful decisions when it comes to their finances. As a result, mobile apps related to finance took longer to penetrate than other verticals such as social, amusement, e-commerce and hospitality. Rapid technology advancements such as Artificial Intelligence (AI), Internet of Things (IoT), etc. require corporates across sectors to transform digitally i.e., technology itself has to be transformed digitally to operate as a business enabler. As far as cyber security of digital transactions is concerned, recently the Reserve Bank of India has permitted card tokenization services which will enable customers to use a third party token requester app like UPI app. Digital transactions through tokenization system would require customers' explicit consent for authentication which is unlikely to be hacked, and hence, would be tantamount to an additional layer of cyber security. Technocrats, finance and banking services experts have been in consensus that new systems forced users to start getting emotionally attached, but due to lack of check and balance mechanism, the system is soon likely to lose its credibility which could lead to detrimental performance. Furthermore, empirical evidence reveals that change of culture is a time-consuming process; gradual switchover to digital transactions using mobile apps is the need of the hour.

6. Limitations

The academic audience should consider a few limitations before deriving any conclusions. *First*, while the author has reviewed e-resources published in English, literature in other languages has been excluded from the scope of the study. Further, only three hypotheses were set; selective variables and limited time frame were considered for conducting the survey. Furthermore, the author has used a self-administered questionnaire, and hence, there is the threat of content validity. Online surveys typically face certain shortfalls; for instance, the respondents have been asked to respond about their saving and spending behaviour after a certain amount of time since their use of mobile apps; the probability of 'exact moment biasness' probably has at least partial influence. *Finally*, the application of inferential statistics could have their own inherent limitations, which has a partial impact on the findings.

7. Practical Implications

The findings of the study have several practical implications for stakeholders. *First*, users of smart phones and tabs may use this research to initiate online purchases by downloading apps on their smart phones through app/play stores and earning discounts or accumulating points for redeeming the same in future shopping. *Second*, frequent travellers and tourists may enjoy hassle-free travels by using online services that are available at lower prices. They may also receive additional discounts on using these app-based services frequently. *Thirdly*, prospective savers may use the report to look for different saving avenues through apps; a number of investment apps such as 'Stash' have been providing comparative features on a single platform. *Fourth*, smart phone users can access lifestyle offerings and financial services seamlessly with a single user id and password through mobile apps such as State Bank of India's recently launched app YONO (You Only Need One), Google Pay, Amazon Pay and PhonePe. They may be used for both household saving and spending. *Finally*, smart phone users may use the report for multiple household spending requirements like payment of equated monthly instalments, life insurance, share trading, matrimonial, entertainment, healthcare services, education, hotel and travel and the like. Banks, online shopping platforms, insurers, etc. may use the report to design new embedded apps by combing big data and artificial intelligence techniques for serving the n-th customer through a single mobile app incorporating lifestyle and financial products.

The study has contributed to existing literature in terms of influence of multiple mobile apps on household saving-spending behaviour in the context of developing economies in general and India in particular. In the Indian context, related literature has validated that young population in the age group of 27-37 years have been significantly accessing smart phones for digital payments (Madan & Yadav, 2016).

The increasing use of cell phones has opened new vistas for digital transactions, a crucial factor for economic growth via exponential growth of corporates in developing economies such as India and China. Research has also shown that use of smart phones, and in turn, mobile apps is not restricted to urban areas. Rural citizens have also taken to online banking and shopping (Chakraborty, 2019), breaking the stigma of restricting banking services access to urban areas only (Mohan & Potnis, 2015) and thereby leading to social changes (Verma & Sinha, 2018). The recent data of growth in Indians' usage of smart phones validates the views of this research. In 2019, the number of Indians using smart phones crossed 502.2 million i.e., around 77 percent of Indians have been using wireless broadband through smart phones, which itself justifies the extensive use of mobile apps for multiple purposes including saving-spending transactions (techARC, 2020). The data validates the findings of the present study indicating that household saving-spending behaviours probably have been significantly influenced by accessing online shopping apps. Furthermore, literature from developed economies validates that data-driven decision making has become complex and apps developers have to consistently introduce innovative apps to meet with customer requirements and intentions (Zhong et al., 2016). The findings of this study that use of apps have significantly impacted saving-spending behaviour calls for continuous innovations for Indian customers. Gathering data about apps users' behaviours and preferences has been a challenge for apps developers in developed countries (Hew et al., 2015). Indian developers can use the findings of this study to address this issue with respect to Indian online consumers.

8. Future Research Roadmap

Future research endeavours should be to integrate unstructured data such as social media with structured data for assessing customer behaviour. The study has adopted cross-sectional design and in future, longitudinal studies may be conducted for comparing apps users' behaviour in saving and spending and in other facets of their lives. Studies may be attempted to explore the possibilities of time series data for tracking individual apps user behaviour which may be used for developing new products and services (Goes, 2014). Moreover, the implementation of big data has been challenged through cultural shock (Ross et al., 2013) which is likely to impact the rampant growth of apps; hence, empirical and qualitative research may be attempted to counter the same. Comparative studies may be attempted to assess the healthcare costs of different countries for developing apps economically since cost is one of the vital determinants of developing health care apps. Research may be undertaken to evaluate how income changes have been taking place state-wise or city-wise by using multiple apps. Impact studies may address efficacy of any dedicated mobile apps such as SBI's YONO, Google's Tez, Paytm, Amazon Pay, BHIM, Money View Loans, CASHE, Fisdom and Qykly in household personal finance behaviour and the outcomes would likely be very useful for stakeholders, especially for policy makers, technocrats, apps users, developers and financial service providers.

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