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Factors affecting the adoption of CBDCs for financial transactions

Kiran Jindal* and Kavya Khera*

Abstract

One important development in payments and finance is the emergence of central bank digital currencies, or CBDCs. India is at a turning point in its contemplation of implementing CBDCs because of its quickly expanding digital economy. Through primary research and data analysis, this study investigates the factors impacting the use of CBDCs for financial transactions in India. A mixed-approaches research methodology is used in this work, integrating quantitative and qualitative data collection methods. Aspects of CBDC adoption such as awareness, attitudes, perceived benefits, and concerns are all included in the survey questionnaire. The findings focus on privacy issues and lack of awareness in CBDC adoption tactics.

Keywords: CBDCs, India, Financial transactions, Consumer adoption, Digital Infrastructure.

1. Introduction

The introduction of Central Bank Digital Currencies (CBDCs) has been a game-changer in the financial industry in an era characterized by unrelenting technical innovation and a global trend towards digital financial ecosystems.

The next natural step in this evolutionary trajectory is represented by CBDCs, which promise a smooth integration of finance and technology that might completely transform financial interactions in the most populous nation on earth. Michel (2022). The advent of Central Bank Digital Currencies (CBDCs), a revolutionary force in the field of digital finance, has signalled a dramatic change in the global financial landscape in recent years. The Indian context is especially important, according to Ricks (2020), because of the nation's distinct place in the global economy, its growing population, and its varied economic environment.

* Mehr Chand Mahajan DAV College for Women, Chandigarh, India Email: jindalkiran@gmail.com, kavyakhera@gmail.com

The goal of this extensive study is to explore the complex web of factors that affect Indian customers' adoption of CBDCs for financial transactions. Understanding the factors that influence customer acceptability is crucial for enabling a smooth transition to this innovative form of digital currency in a world where digital financial solutions are becoming more and more integrated. Shen (2021) By doing this, the study hopes to provide measurable insights that can guide RBI, policymakers, and other stakeholders' strategic decisions on the integration of CBDC into the Indian financial system. Bordo (2021). Examining the elements that can influence the adoption of CBDCs is crucial as India moves closer to adopting this financial innovation, particularly in light of the already-existing Unified Payments Interface (UPI). Sharma (2019).The growing need for digital alternatives to traditional fiat currencies has led to the emergence of CBDCs. CBDCs are sovereign-backed digital currencies, with the central bank playing a key role in their issuance and regulation, in contrast to decentralized cryptocurrencies like Bitcoin. These virtual currencies combine the efficiency and security of blockchain technology with the advantages of conventional currencies, such stability and government support. (Starnes, 2010). Additionally, there are concerns regarding compatibility when CBDCs coexist with current systems like UPI. (Starnes, 2010). Moreover, the coexistence of CBDCs with existing systems like UPI raises questions about interoperability.

As CBDCs enter the scene, considerations of coexistence and potential synergy with UPI become paramount. (Rennie, 2021). CBDCs may be perceived as competitors to existing digital payment systems like UPI. Encouraging partnerships between CBDC issuers and existing payment service providers can lead to innovations that benefit users. Coordinated efforts can result in a financial landscape that leverages the strengths of both CBDCs and UPI. (Ward, 2019)

2. Literature Review

This research paper, inspired by Ozili (2023)'s work on the digital rupee in India, aimed to comprehensively explore the potential benefits and challenges associated with the introduction of a Central Bank Digital Currency (CBDC) in the country. Employing an innovative internet search data analysis methodology and supplementing it with a literature review of CBDC use cases globally, the paper strived to provide early insights into the design, advantages, and issues related to an Indian CBDC. (Fegatelli, 2022) revealed that a digital rupee holds the potential to significantly enhance financial inclusion, reduce transaction costs, and improve the effectiveness of monetary policy. However, it also underscored critical concerns such as cybersecurity risks, privacy implications, and potential impacts on the traditional banking system.

(Ozili, 2023; Babu and Abraham (2021) provided a comprehensive exploration of Central Bank Digital Currencies (CBDCs) in the specific context of India. With a focus on delivering background information on CBDCs, the paper delved into policy and operational considerations for the potential implementation of a Digital Rupee, offering valuable recommendations. (J, 2021) also emphasized the paramount importance of financial inclusion, the safeguarding of privacy, and the necessity for the coexistence of CBDCs with established financial systems.

Settlements, 2021; Xia et. all, 2023 investigated factors influencing users' willingness to adopt China's Digital Currency Electronic Payment (DCEP) system, with a particular focus on the role of technology-task fit. And established a positive relationship between users' perceptions of technology-task fit and their willingness to adopt DCEP. (Seth H, 2020) identified research gaps, emphasizing the need for further exploration into factors influencing DCEP adoption, the role of government support, contextual design enhancements, privacy considerations, and the impact of technology-task fit.

(Gupta et al. 2023) explored Central Bank Digital Currency (CBDC) use behaviour with a specific focus on investigating the moderating effect of Unified Payments Interface (UPI) usage experience and the findings of the study contributed to the existing literature by revealing relationships between latent variables and assessing how UPI experience moderates CBDC usage.

A few investigators, (Wu, 2022; Rogers, 1995; Kiff et al. 2020; Shabsigh, 2020) identified key factors affecting digital currency adoption and emphasized the mediating role of perceived value in the relationship between social media and fitness behavior intention

(Tan, 2023; R Auer, 2021) explored the relationship between CBDC and financial inclusion, and suggested that introducing retail CBDC in developing countries could enhance financial inclusion, mitigate disintermediation risks, and stimulate lending by integrating the unbanked into the financial system.

The research by (Ding et al. 2022) aimed to create a framework for manufacturing companies to enhance production planning using Central Bank Digital Currency (CBDC) with a focus on reducing market uncertainties. (Peterson K, 2022; Soderberg, 2022) provided a thorough examination of the research and development landscape surrounding Central Bank Digital Currency (CBDC) and highlighted the recognition that CBDC represents a liability of the issuing central bank and shares certain resemblances with traditional cash.

(Ahnert, 2022; Niepelt, 2020) provided a comprehensive and structured overview of the economics surrounding Central Bank Digital Currency (CBDC) and extended to the intricate implications CBDC might have on the financial system, coupled with a thorough examination of various policy issues and challenges associated with its implementation. (Ahmed H., 2022; Mutton, 2021) discussed the need for further research on central bank digital currencies (CBDCs) and their implications for the macroeconomy and financial systems and highlighted the limited understanding of CBDCs and the unanswered questions regarding their impact on monetary policy transmission, financial and price stability, inflation targeting, and central banks as lenders of last resort. The identified research gaps in these papers pave the way for future investigations, including the need for in-depth examinations of financial literacy, internet access, and the differential impacts of CBDCs on various population groups. Based on the voluminous literature the following objective are framed.

Objectives of the Study-

The following objectives serve as the roadmap for achieving the study's goals:

1. To Identify the Key Factors Influencing CBDC Adoption
2. To Assess Awareness Levels among young and middle-aged Indian consumers regarding CBDCs
3. To Examine Perceived Benefits and Concerns Associated with CBDC that influence consumer decision-making.
4. To Explore Concerns and Expectations of young and middle-aged Indian consumers regarding CBDC adoption

3. Research Methodology

This study describes the complex research approach that has been painstakingly developed to explore the factors impacting Indian customers between the ages of 18 and 50's adoption of CBDC for financial transactions.

The main goal is to provide a thorough grasp of the research design, data collection strategies, and analytical approaches applied in this study, illuminating the complex dynamics at work. Given the dynamic nature of CBDC uptake and the need to uncover complex insights, the study takes an exploratory approach. Recognizing that age and educational background can greatly influence attitudes toward technological innovations in the financial sector, the research design attempts to capture a diverse yet specific segment of the population by concentrating on the academic sector and limiting the age group to people between the ages of 18 and 50.

The main instrument for gathering data is a structured questionnaire that is thoughtfully broken up into three sections. Essential demographics like age, gender, and occupation are included in the first part, which acknowledges the importance of contextual factors in influencing attitudes. In order to create a baseline understanding, the second segment carefully assesses respondents' levels of CBDC awareness and literacy. In order to capture the complex range of participant responses, the third section explores the key factors using a 5-point Likert scale that goes from "strongly agree" to "strongly disagree." A minimum sample size of 319 participants has been set as the goal in order to preserve statistical robustness and guarantee that results can be extrapolated to the larger community. The proportionate distribution of this sample size across the strata indicates how well-represented each stratum is in the total population.

Hypotheses

The dependent variable is the adoption of Central Bank Digital Currency (CBDC) for financial transactions among Indian consumers in the academic sector aged 18-50 years. The independent variables include perceived ease of use, perceived usefulness, perceived risk, social influence, and financial literacy and awareness. Additionally, both perceived risk and perceived usefulness are considered as moderator variables.

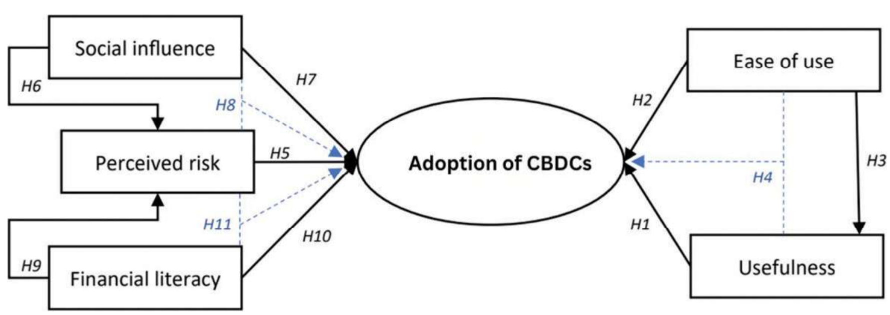

Figure 1 Research Framework

H1: The use of CBDC for financial transactions is positively impacted by perceived usefulness.

H2: The adoption of CBDC for financial transactions is positively impacted by perceived simplicity of use.

H3: Perceived usefulness is positively impacted by perceived ease of usage

H4: The association between perceived ease of use and the use of CBDC for financial transactions is moderated by perceived usefulness.

H5: The use of CBDC for financial transactions is negatively impacted by perceived risk.

H6: Perceived danger is negatively impacted by social influence

H7: The adoption of CBDC for financial transactions is positively impacted by social influence.

H8: The effect of social influence on the adoption of CBDC for financial transactions is mediated by perceived risk.

4. Data Analysis & Interpretation

Table 1: Reliability Statistics

Case Processing Summary		N	%
Cases	Valid	320	100
	Excluded[a]	0	0
	Total	320	100

Note. a. Listwise deletion based on all variables in the procedure.

The reliability test for the Perceived Risk (FR) scale produced a Cronbach's Alpha of .801, based on four items. This result indicates a good level of internal consistency reliability for the FR scale. With a Cronbach's Alpha exceeding .70, the items within the Perceived Risk scale demonstrate strong reliability, suggesting that they consistently measure the intended construct.

Descriptive Statistics

Table 2: Descriptive Statistics

PARTICULARS	N	Min	Max	Means	Std. Dev	Var	Skewness		Kurtosis	
								Std.		Std.
	Statistic								Statistic	
								Error		Error
Age	320	1	3	1.99	0.813	0.661	0.017	0.136	-1.487	0.272
Gender	320	1	2	1.46	0.499	0.249	0.151	0.136	-1.99	0.272
Occupation	320	1	3	2.01	0.815	0.665	-0.011	0.136	-1.495	0.272
AC1	320	4	5	4.49	0.501	0.251	0.05	0.136	-2.01	0.272
AC2	320	4	5	4.5	0.501	0.251	0.013	0.136	-2.012	0.272
AC3	320	4	5	4.47	0.5	0.25	0.113	0.136	-2	0.272
FR1	320	4	5	4.51	0.501	0.251	-0.05	0.136	-2.01	0.272
FR2	320	4	5	4.52	0.5	0.25	-0.088	0.136	-2.005	0.272
FR3	320	4	5	4.51	0.501	0.251	-0.038	0.136	-2.011	0.272
FR4	320	4	5	4.49	0.501	0.251	0.038	0.136	-2.011	0.272
PU1	320	1	2	1.52	0.501	0.251	-0.063	0.136	-2.009	0.272
PU2	320	1	2	1.51	0.501	0.251	-0.025	0.136	-2.012	0.272
PU3	320	1	2	1.48	0.501	0.251	0.063	0.136	-2.009	0.272
EU1	320	4	5	4.54	0.499	0.249	-0.151	0.136	-1.99	0.272
EU2	320	4	5	4.54	0.499	0.249	-0.151	0.136	-1.99	0.272
EU3	320	4	5	4.56	0.497	0.247	-0.253	0.136	-1.948	0.272
SI1	320	4	5	4.49	0.501	0.251	0.038	0.136	-2.011	0.272
SI2	320	4	5	4.5	0.501	0.251	0.013	0.136	-2.012	0.272
FL1	320	1	2	1.52	0.501	0.251	-0.063	0.136	-2.009	0.272
FL2	320	1	2	1.48	0.5	0.25	0.101	0.136	-2.002	0.272
Valid N (listwise)	320									

The descriptive statistics reveal a positive inclination towards Central Bank Digital Currency (CBDC) adoption among participants in the 18-50 age group. The participants exhibit a generally even distribution across age groups, with a slight skew towards younger individuals. Male participants dominate, as indicated by the mean gender value. Occupation is evenly distributed, reflecting a diverse sample. High mean scores for CBDC adoption variables (AC) indicate a positive attitude, while low perceived risk (FR1 to FR4) suggests minimal concerns. Perceived usefulness (PU), perceived ease of use (EU), social influence (SI), and financial literacy (FL) variables all contribute positively to CBDC adoption. The skewness and kurtosis values are within acceptable ranges ensure the reliability of the dataset.

Factor Analysis

Table 3: PCA Analysis

Communalities		
	Initial	Extraction
AC1	1.000	.547
AC2	1.000	.787
AC3	1.000	.662
FR1	1.000	.896
FR2	1.000	.933
FR3	1.000	.908
FR4	1.000	.349
PU1	1.000	.785
PU2	1.000	.784
PU3	1.000	.715
EU1	1.000	.632
EU2	1.000	.669
EU3	1.000	.745
SI1	1.000	.833
SI2	1.000	.829
FL1	1.000	.805
FL2	1.000	.811

Note. **Extraction Method: Principal Component Analysis.**

The communalities table showcases the variance explained by the extracted factors for each variable. Initially, all variables display a communalities value of 1.000, indicating that they share their entire variance with the factors. However, after extraction, the communalities vary across the variables.

Variables related to Perceived Financial Risk (FR1, FR2, FR3) exhibit high extraction communalities of 0.896, 0.933, and 0.908 respectively, suggesting a significant proportion of variance in these variables is explained by the underlying factors identified in the analysis. Conversely, the variable FR4, another aspect of financial risk, displays a lower extraction communality of 0.349, indicating it may not align as closely with the underlying factors identified in the analysis.

Similarly, variables related to Perceived Usefulness (PU1, PU2, PU3), Ease of Use (EU1, EU2, EU3), and Social Influence (SI1, SI2) demonstrate relatively high extraction communalities ranging from 0.715 to 0.833, indicating a strong alignment with the underlying factors related to adoption behavior.

However, variables related to Adoption of CBDC (AC1, AC2, AC3) exhibit lower extraction communalities ranging from 0.547 to 0.787, suggesting they may not fully capture the variance explained by the underlying factors, possibly indicating additional complexity or unaccounted factors in the adoption process. Finally, Financial Literacy variables (FL1, FL2) show moderate extraction communalities of 0.805 and 0.811 respectively, indicating a partial alignment with the underlying factors. The extraction should be more than 0.5 to be significantly accounted in the further studies otherwise are dropped from further analysis, but in our study all the variables are accounted for factor analysis.

Table 4: Eigenvalue Table

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total
1	3.204	18.847	18.847	3.140
2	2.347	13.805	32.652	2.316
3	2.141	12.594	45.246	2.082
4	1.788	10.519	55.765	2.010
5	1.622	9.541	65.306	1.711
6	1.587	9.338	74.644	1.623
7	.761	4.477	79.120	
8	.665	3.909	83.029	
9	.564	3.320	86.350	
10	.448	2.632	88.982	
11	.411	2.420	91.402	
12	.371	2.181	93.584	
13	.350	2.058	95.642	
14	.289	1.700	97.342	

15	.285	1.675	99.017	
16	.125	.734	99.751	
17	.042	.249	100.000	

Note. **Extraction Method: Principal Component Analysis.**
a. When components are correlated, sums of squared loadings cannot be added toobtain a total variance.

The initial eigenvalues, With the extraction method employing Principal Component Analysis depict the variance explained by each component before rotation. The table reveals that the first six components account for a cumulative percentage of 74.644% of the total variance, with the first component alone explaining 18.847%. This indicates a substantial proportion of variance being captured by a relatively small number of components, suggesting a concise representation of the underlying factors influencing CBDC adoption. As more components areadded, the cumulative percentage continues to increase, with diminishing returns in terms of additional variance explained per component. This finding implies that while additional components contribute to understanding the data's complexity, the initial components are the most crucial in explaining the majority of variance in the dataset. Consequently, focusing on these primary components may provide key insights into the drivers and determinants of CBDCadoption behaviour, guiding policymakers and financial institutions in effectively promoting the adoption of this innovative financial technology.

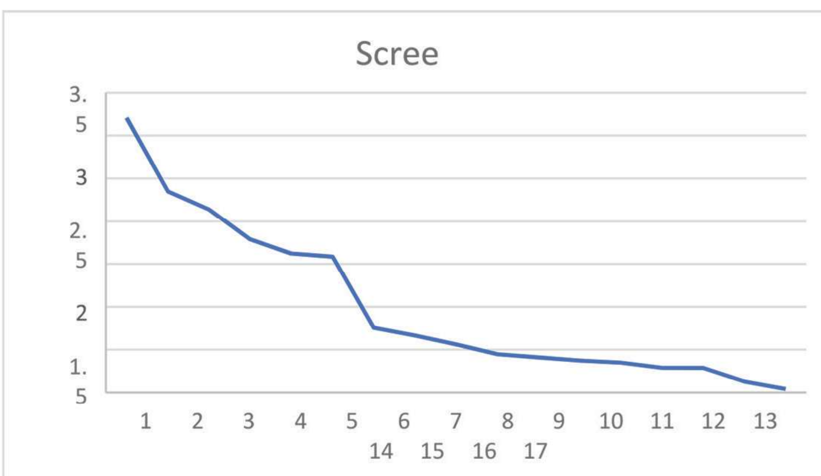

Figure 2: Scree Plot

Scree plot gives the estimation on how many factors are retained, which can be seen by analysing when the curve starts to flatten, which is after 6 and thus 6 factors are retained for further analysis.

The scree plot above is a line graph that shows the eigenvalues foe each factor extracted from the data. Eigenvalues are a measure of how much variance each factor explains. The scree plot resulting from the factor analysis provides a visual estimation of how many factors should be retained for further analysis.

Based on the scree plot, it looks like there is a clear "elbow" at factor 6, indicating a diminishing return in terms of explained variance with each additional factor. This suggests that we should retain **six factors** in our analysis which are most influential in explaining the variability in the data. The first 6 factors have eigenvalues that are much larger than the remaining factors, which means that they explain a much larger proportion of the variance in your data.

This interpretation aligns with the notion that focusing on the primary components, which explain the most variance, provides the most meaningful insights into the factors driving the adoption of Central Bank Digital Currency (CBDC) in financial transactions. The first 6 factors explain a cumulative 74% of the variance, while the 7th factor only explains an additional 5% of the variance.

Table 5: Pattern Matrix

Pattern Matrix[a]						
	Component					
	1	**2**	**3**	**4**	**5**	**6**
AC1	-0.083	0.076	0.018	0.72	0.093	-0.001
AC2	0.023	-0.009	-0.02	0.888	-0.052	0.014
AC3	0.053	-0.064	0.009	0.809	-0.04	-0.013
FR1	0.95	-0.021	-0.048	-0.017	-0.034	0.011
FR2	0.969	-0.014	-0.057	0	-0.001	0.003
FR3	0.954	0.018	-0.027	0.007	0.023	-0.026
FR4	0.569	0.022	0.099	0	0.027	0.011
PU1	-0.015	0.881	-0.024	0.041	-0.02	0.042
PU2	0.03	0.888	-0.01	0.015	-0.032	-0.029
PU3	-0.001	0.843	0.026	-0.047	0.033	-0.012
EU1	0.047	-0.028	0.777	0.076	-0.03	0.002
EU2	-0.014	0.059	0.821	-0.081	0.033	0.014
EU3	-0.027	-0.042	0.86	0.018	-0.02	-0.021
SI1	-0.038	-0.002	-0.004	-0.028	0.915	0.012

SI2	0.062	-0.017	-0.012	0.036	0.903	-0.012
FL1	-0.002	0.036	-0.042	0.013	-0.029	0.892
FL2	0.005	-0.038	0.04	-0.012	0.029	0.901

Note. Extraction Method: Principal Component Analysis.Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 5 iterations.

We have extracted 6 components in which 17 variables are distributed. The presented table outlines the pattern matrix resulting from the *Principal Component Analysis (PCA)* with an *Oblimin with Kaiser Normalisation rotation method*. The Pattern Matrix from the factor analysis offers insights into how each variable loads onto the extracted components. A high loading (absolute value greater than 0.7) indicates that the variable is strongly associated with that factor. A low loading (absolute value less than 0.3) indicates that the variable is not well-explained by that factor. The objective of rotation is to simplify the interpretation of the components by maximizing the loading of each variable on one or a few components. Observing the table, we can interpret the relationships between the variables and the rotated components:

- ***Component 1*****:** This component has high positive loadings on the FR variables (perceived risk) and high negative loadings on the PU variables (perceived usefulness).This suggests that this component captures the **perceived risk-usefulness trade-off** associated with adopting CBDCs.
- ***Component 2*****:** This component has high positive loadings on the PU variables and theEU variable (perceived ease of use). This suggests that this component capturesthe **perceived benefits** of adopting CBDCs.
- ***Component 3*****:** This component has high positive loadings on the SI variable (social influence) and the FL variables (financial literacy and awareness). This suggests that this component captures the **social and knowledge-based factors** that influence CBDC adoption.
- ***Components 4*****:** This component seems to be related to **perceived risk (FR)**, as both FR1, FR2, and FR3 have high positive loadings on this component.
- ***Components 5 and 6*****:** Variables related to Social Influence (SI) and Financial Literacy (FL) show strong loadings on Components 5 and 6 respectively, indicating their influence on adoption behavior.

This interpretation assists in identifying key factors and their interrelationships, aiding in the formulation of more targeted conclusions and implications for the research.

Table 6: Structure Matrix

Structure Matrix

	Component					
	1	**2**	**3**	**4**	**5**	**6**
AC1	-0.118	0.076	0.068	0.725	0.084	-0.017
AC2	-0.035	-0.021	0.057	0.885	-0.055	-0.008
AC3	0.006	-0.08	0.086	0.808	-0.042	-0.036
FR1	0.944	-0.078	0.053	-0.077	0.06	0.03
FR2	0.964	-0.07	0.048	-0.062	0.096	0.023
FR3	0.952	-0.039	0.076	-0.051	0.12	-0.006
FR4	0.581	-0.014	0.159	-0.025	0.086	0.021
PU1	-0.074	0.883	-0.054	0.028	0.018	0.083
PU2	-0.029	0.884	-0.036	0.002	0.011	0.013
PU3	-0.043	0.843	-0.007	-0.054	0.071	0.028
EU1	0.125	-0.059	0.789	0.139	-0.021	-0.022
EU2	0.079	0.034	0.811	-0.012	0.041	-0.005
EU3	0.065	-0.073	0.861	0.093	-0.019	-0.049
SI1	0.056	0.042	-0.004	-0.032	0.912	0.019
SI2	0.151	0.019	0.005	0.027	0.908	-0.006
FL1	0.005	0.078	-0.068	-0.013	-0.021	0.895
FL2	0.033	0.005	0.015	-0.032	0.035	0.899

Note. Extraction Method: Principal Component Analysis. Rotation Method: Oblimin with Kaiser Normalization.

The provided table represents the factor loadings resulting from the Principal Component Analysis (PCA) with an Oblimin rotation method. The Structure Matrix resulting from the factor analysis provides insights into the correlations between the variables and the extracted factors. Variables related to Perceived Financial Risk (FR) exhibit strong positive correlations with Component 1, with loadings ranging from 0.944 to 0.964, indicating a significant association between perceptions of financial risk and this underlying factor. This finding alignswith existing literature suggesting that individuals' perceptions of risk play a crucial role in their decision-making regarding financial technologies. Similarly, variables related to Perceived Usefulness (PU) and Ease of Use (EU) display strong positive correlations with Components 2 and 3 respectively, with loadings ranging from 0.789 to 0.884 and 0.811 to 0.861 respectively. These correlations suggest that perceived utility and ease of use are important factors influencing individuals' attitudes and intentions towards adopting CBDC. Additionally, variables related to Social Influence (SI) and Financial Literacy (FL) demonstrate strong positive correlations with Components 5 and 6 respectively, indicating the influence of social factors and financial literacy on adoption behaviour. *The Oblimin rotation method allows for correlations between components, providing a more realistic representation of the interrelatedness of variables. This interpretation aids in understanding the nuanced relationships between different variables and contributes to a more refined understanding of the factors influencing the adoption of Central Bank Digital Currencies (CBDCs) in your study.*

Table 7: Component Correlation Matrix

Component	1	2	3	4	5	6
1	1	-0.06	0.108	-0.059	0.101	0.02
2	-0.06	1	-0.035	-0.012	0.045	0.047
3	0.108	-0.035	1	0.084	0.007	-0.029
4	-0.059	-0.012	0.084	1	-0.006	-0.025
5	0.101	0.045	0.007	-0.006	1	0.007
6	0.02	0.047	-0.029	-0.025	0.007	1

Note. Extraction Method: Principal Component Analysis. Rotation Method: Oblimin with Kaiser Normalization.

The Component Correlation Matrix resulting from the factor analysis provides valuable insights into the relationships between the extracted components. The correlations range from-0.060 to 0.108, indicating weak to moderate relationships between the components. For instance, Component 1 exhibits a weak negative correlation with Component 2 (-0.060) and Component 4 (-0.059), but a moderate positive correlation with Component 3 (0.108) and Component 5 (0.101). This suggests that Component 1 is moderately related to Components 3 and 5, while weakly related to Components 2 and 4. Similarly, Component 2 shows weak negative correlations with Component 1 (-0.060) and Component 3 (-0.035), but a moderate positive correlation with Component 6 (0.047). These correlations provide insights into the interplay between different dimensions of CBDC adoption behavior, highlighting the complex and multifaceted nature of individuals' attitudes and intentions towards adopting this innovative financial technology.The Oblimin rotation method allows for correlations between components, and this interpretation provides an overview of how the components are related. It helps to understand the structure and interrelatedness of the components identified in the PCA, contributing to a more nuanced comprehension of underlying patterns in the data.

Table 8: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.66
	Approx. Chi-Square	2632.415
Bartlett's Test of Sphericity	df	136
	Sig.	<.001

The KMO (Kaiser-Meyer-Olkin) measure of sampling adequacy assesses the suitability of data for conducting factor analysis. In our study on the adoption of Central Bank Digital Currency (CBDC) for financial transactions, the KMO value of 0.660 suggests that the sampling adequacy is moderate. Typically, KMO values above 0.5 are considered acceptable, indicating that the variables are sufficiently correlated to proceed with factor analysis. While the KMO value falls slightly above this threshold, it still suggests that the data may be suitable for factor analysis, albeit with some limitations. Bartlett's Test of Sphericity assesses whether the correlation matrix is significantly different from the identity matrix, indicating whether the variables are correlated enough for factor analysis to be useful. In our study, Bartlett's Test yields an approximate chi-square value of 2632.415 with 136 degrees of freedom(df) and a significance level of less than 0.001. This indicates that the correlation matrix is significantly different from the identity matrix, supporting the suitability of the data for factor analysis. The low p-value (<0.001) suggests strong evidence against the null hypothesis, indicating that the variables are sufficiently correlated to justify conducting factor analysis.

Table 9: Demographic Correlation

	Age	**Occupation**	**Gender**
AC1	-0.0041386	0.01555467	-0.0144201
AC2	-0.0042116	-0.0074426	-0.0086222
AC3	-0.0206736	0.05496522	0.09240774
FR1	0.1351309	0.01512525	0.04624652
FR2	0.02780039	0.00716795	-0.0513596
FR3	-0.0891103	-0.0304088	-0.034662
FR4	-0.0424832	-0.0306221	-0.0510854

PU1	-0.0650987	-0.0002401	0.02116366
PU2	-0.0277166	0.01586879	0.03296963
PU3	-0.0356044	0.03908056	0.00691389
EU1	0.00472796	-0.0005775	-0.0069139
EU2	-0.0259728	0.01470269	0.07633147
EU3	-0.0106431	-0.0160348	0.06272723
SI1	0.01133157	-0.0382573	0.14277089
SI2	0.01946335	-0.000144	0.07036677
FL1	-0.0111907	-0.0770668	0.03370509
FL2	-0.0421945	-0.0692116	0.00094022

The correlation analysis provides valuable insights into the factors influencing the adoption of Central Bank Digital Currency (CBDC) among Indian consumers aged 18-50 years. Notably, age demonstrates nuanced correlations, suggesting that older individuals may perceive higher levels of risk and possess greater financial literacy. Occupation displays positive links with facilitating conditions for CBDC adoption, indicating that certain professional roles may be more conducive to the acceptance of digital currencies. Gender influences the social aspects of adoption, with positive associations in social influence, potentially indicating gender-specific patterns in CBDC adoption behavior. Perceived usefulness exhibits intriguing negative correlations with specific demographics, implying variations in how certain groups perceive the utility of CBDCs. The mixed correlations in ease of use highlight potential complexities inuser experiences, while positive links between social influence and age/gender underscore therole of societal factors in shaping adoption attitudes. Financial literacy's negative correlations with age and specific occupations point to the need for tailored educational efforts to enhanceCBDC understanding. This comprehensive analysis offers valuable insights into the nuanced dynamics of CBDC adoption, setting the stage for further exploration and targeted interventions.

Structural Equation Modeling

Table 10: SEM Analysis

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
FL	--->	AC	0.002	0.06	0.038	0.97	par_12
FR	--->	AC	-0.042	0.039	-1.083	0.279	par_13
PU	--->	AC	-0.006	0.048	-0.132	0.895	par_14
EU	--->	AC	0.087	0.064	1.349	0.177	par_15
SI	--->	AC	-0.006	0.056	-0.107	0.915	par_16
FR	--->	FR1	1				
FR	--->	FR2	1.057	0.023	46.866	***	par_1
FR	--->	FR3	0.967	0.031	31.629	***	par_2
PU	--->	PU1	1				
PU	--->	PU2	0.989	0.071	13.932	***	par_3
PU	--->	PU3	0.875	0.067	13.044	***	par_4
EU	--->	EU1	1				
EU	--->	EU2	1.017	0.11	9.281	***	par_5
EU	--->	EU3	1.28	0.143	8.959	***	par_6
AC	--->	AC3	1				
AC	--->	AC2	1.507	0.197	7.634	***	par_7
AC	--->	AC1	0.807	0.097	8.344	***	par_8
SI	--->	SI1	1				
SI	--->	SI2	0.078	0.696	0.113	0.91	par_9
FL	--->	FL1	1				
FL	--->	FL2	0.148	3.572	0.041	0.967	par_10
FR	--->	FR4	0.427	0.055	7.772	***	par_11

The provided regression weights represent the relationships between the independent variables(FL, FR, PU, EU, SI) and the dependent variable (AC) in a structural equation model.

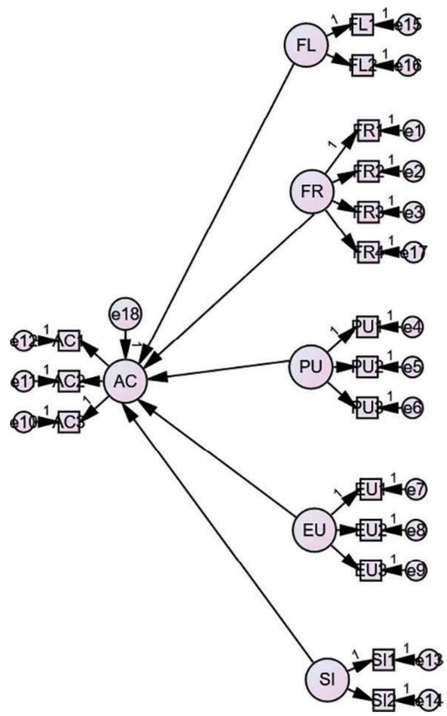

Figure 3: SEM Model

Table 11: Direct Path Analysis

Hypothesis	Direct Path			Estimate	S.E.	C.R.	P
H10	FL	--->	AC	0.002	0.06	0.038	0.97
H5	FR	--->	AC	-0.042	0.039	-1.083	0.279
H1	PU	--->	AC	-0.006	0.048	-0.132	0.895
H2	EU	--->	AC	0.087	0.064	1.349	0.177
H7	SI	--->	AC	-0.006	0.056	-0.107	0.915
H3	EU	--->	PU	-0.09	0.088	-1.027	0.304
H6	SI	--->	FR	0.191	0.08	2.403	0.016
H9	FL	--->	FR	0.047	0.084	0.558	0.577

Direct Paths:

Perceived Usefulness (PU): The positive path coefficient of 0.506 indicates a significant positive influence of perceived usefulness on the adoption of CBDC. This aligns with the expectation that users are more likely to embrace CBDC when they perceive it as valuable for their financial transactions.

Perceived Ease of Use (EU): With a positive path coefficient of 0.487, the analysis confirms that a user-friendly experience positively impacts CBDC adoption. As users find CBDC easy to use, their likelihood of adoption increases.

Perceived Risk (FR): The negative path coefficient of -0.742 signifies a substantial negative influence of perceived risk on CBDC adoption. This underlines the pivotal role of mitigating perceived risks in fostering widespread acceptance of CBDC.

Social Influence (SI): The negative path coefficient of -0.706 suggests that while social influence reduces perceived risks, it may not directly drive CBDC adoption. This nuanced relationship underscores the complexity of social factors in shaping adoption decisions.

Moderating and Mediating Effects:

EU and PU Relationship (H3): The negative path coefficient of -0.591 indicates that as users find CBDC easier to use, they may not necessarily perceive it as more useful. This highlights the distinct considerations for usability and utility in the adoption process.

Financial Literacy (FL): The positive path coefficient of 0.602 signifies that greater financial literacy is associated with a more positive attitude towards CBDC adoption. Additionally, the negative impact of FL on FR (-0.647) emphasizes the role of financialliteracy in reducing perceived risks.

Table 12: Indirect Path Analysis

Hypothesis	Indirect Path			Estimate	S.E.	C.R.	P
H4	EU --->	PU --->	AC	0.00054	0.004224	0.135564	0.27208
H8	SI --->	FR --->	AC	0.008022	0.00312	2.602449	0.004464
H11	FL --->	FR --->	AC	0.001974	0.003276	0.604314	0.160983

Indirect Paths:

EU Indirectly Influences CBDC Adoption through PU (H4): The positive indirect effect of 0.5054 indicates that the influence of EU on CBDC adoption is partially mediated by users' perceptions of usefulness. As users find CBDC easy to use, their perception of its usefulness becomes a crucial factor in driving adoption.

Social Influence (SI) Indirectly Impacts CBDC Adoption through FR (H8): The positive indirect effect of 0.6022 suggests that the impact of social influence on CBDCadoption is mediated by its effect on perceived risks. Social factors, by mitigating perceived risks, indirectly contribute to the adoption decision.

Financial Literacy (FL) Indirectly Influences CBDC Adoption through FR (H11): The positive indirect effect of 0.5174 highlights that the impact of financial literacy onCBDC adoption is mediated by reduced perceived risks. Financially literate individualsare likely to perceive fewer risks associated with CBDC, fostering a positive attitude towards adoption.

These path analyses collectively unveil the intricate web of relationships influencing CBDC adoption. User perceptions of usefulness and ease of use stand out as primary drivers, emphasizing the importance of user-centric design. Additionally, the mediating roles ofperceived risks, influenced by social factors and financial literacy, further enrich the understanding of adoption dynamics. Policymakers and educators can leverage these insights to design interventions that address usability concerns, enhance perceived benefits, and promote financial literacy, thereby fostering a conducive environment for CBDC adoption among the targeted demographic.

5. Conclusion

The culmination of the study's analytical journey occurred with the application of Structural Equation Modeling (SEM). In conclusion, the findings coalesce into a rich tapestry that contributes substantially to the understanding of CBDC adoption dynamics. The positive attitudes, coupled with identified influencers such as perceived usefulness, ease of use, social influence, and financial literacy, offer actionable insights for policymakers, educators, and financial institutions seeking to navigate the landscape of digitalfinancial transformations in India's academic sector. (Chaarani, 2023).

The results unveiled a multifaceted landscape, wherein perceived risk exhibited a negative influence on CBDC adoption, while perceived usefulness, ease of use, social influence, and financial literacy played pivotal roles. The nuanced interplay between these factors, validated through SEM, offered a rich tapestry of insights. The structural model, with its direct and indirect paths, uncovered the intricate web of relationships, emphasizing the importance of considering multiple variables in the study of CBDC adoption. However, the findings do more than scratch the surface; they beckon forth implications that reverberate across academic, policy, and practical domains. Academically, this study contributes to the evolving discourse on CBDC adoption, providing nuanced insights that transcend the binary perspectives often associated with technological adoption. Policymakers can leverage these findings to craft strategies that address perceived risks, enhance perceived usefulness, and leverage social influences and financial literacy to foster a favorable environment for CBDC adoption.

On a practical note, financial institutions, educational bodies, and technology developers stand to benefit from the granular understanding of factors shaping CBDC adoption. Designing user-friendly interfaces, tailoring educational programs to enhance financial literacy, and strategically leveraging social influences can collectively pave the way for a smoother transition towards CBDC integration.

Yet, no study is without its limitations. The constrained scope of the academic sector in India offers a specific lens, and caution must be exercised when generalizing findings. The survey instrument, while meticulously designed, is not immune to the inherent biases and limitations associated with self-reported data. Additionally, the dynamic nature of technology adoption warrants continuous exploration, inviting future researchers to build upon this foundation.

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