Factors Influencing Behavioural Intention To Use DigiLocker Among Users In Mangaluru City: An Extended Technology Acceptance Model Approach

Dr. Raghavendra[1], Shruthi N[2]

[1]Faculty of Commerce, University Evening College, Mangaluru.

ORCID ID: 0000-0002-2130-2476; Email ID: dr.raghavendra23@gmail.com

[2]Guest Faculty in Commerce & Management, University First Grade College, Mangalagangothri.

Email ID: shru.n1991@gmail.com

Area of the Paper: Management
Type of the Paper: Regular Paper
Type of Review: Peer Reviewed as per |C|O|P|E| guidance.
Indexed In: OpenAIRE.
DOI: https://doi.org/10.5281/zenodo.14854760
Google Scholar Citation: IJCSBE

How to Cite this Paper:
Dr. Raghavendra & Shruthi, N. (2025). Factors Influencing Behavioural Intention To Use DigiLocker Among Users In Mangaluru City: An Extended Technology Acceptance Model Approach. *International Journal of Case Studies in Business, IT, and Education (IJCSBE), 9*(1), 1-19. DOI: https://doi.org/10.5281/zenodo.14854760

International Journal of Case Studies in Business, IT and Education (IJCSBE)
A Refereed International Journal of Srinivas University, India.
Crossref DOI: https://doi.org/10.47992/IJCSBE.2581.6942.03679

Received on : 14/11/2024
Published on : 12/02/2025

Factors Influencing Behavioural Intention To Use DigiLocker Among Users In Mangaluru City: An Extended Technology Acceptance Model Approach

Dr. Raghavendra[1], Shruthi N[2]

[1]Faculty of Commerce, University Evening College, Mangaluru.

ORCID ID: 0000-0002-2130-2476; Email ID: dr.raghavendra23@gmail.com

[2]Guest Faculty in Commerce & Management, University First Grade College, Mangalagangothri.

Email ID: shru.n1991@gmail.com

ABSTRACT

Purpose: *The factors influencing behavioural intention to use (BIU) were examined in this study. DigiLocker, a digital storage platform offered by the Indian government, among individuals in Mangaluru City. This study explored crucial constructs, including Perceived Usefulness (PU), Perceived Ease of Use (PEOU), self-efficacy (SE), and Social Influence (SI), to ascertain their effects on users' adoption intentions.*

Design/methodology/approach: *A survey-based quantitative methodology encompassing 200 DigiLocker users in Mangaluru was employed. Structural Equation Modelling (SEM) was utilised to analyse the relationships among PU, PEOU, SE, SI, and BIU within the Technology Acceptance Model (TAM) framework.*

Findings: *The results show that all four factors PU, PEOU, SE, and SI significantly influenced BIU. PU emerged as the most robust predictor, demonstrating that users valued the platform's perceived benefits. PEOU also significantly impacted BIU, albeit to a lesser extent than PU, suggesting that ease of use is an essential but secondary motivator. SE significantly contributes to BIU, indicating that users' confidence in their digital abilities fosters their adoption. While significant, SI exhibits a moderate influence on BIU, implying that social endorsements are less critical than individual perceptions of utility and usability.*

Practical implications: *The findings indicate that DigiLocker developers and policymakers should prioritise enhancing the platform's practical benefits and user-friendliness to facilitate broader adoption. Furthermore, the provision of support resources could potentially augment user self-efficacy, aligning with the user requirements for competence and confidence in utilising digital platforms.*

Originality/value: *This study contributes to digital adoption literature by examining DigiLocker acceptance in an urban Indian context, providing insights for policymakers regarding the significance of practical benefits over social factors in technology adoption.*

Type of the paper: *Original Article*

Keywords: Technology Acceptance Model (TAM), DigiLocker, Behavioural Intention to Use (BIU), Structural Equation Modelling (SEM), Digital Adoption

1. INTRODUCTION:

Technology breakthroughs and government-led programs like DigiLocker have fuelled a major digital transformation in the financial services industry. Launched by the Indian government, DigiLocker offers a secure and efficient digital platform for storing and sharing personal documents and enhancing transparency, accessibility, and efficiency in public service delivery. This initiative is part of a broader e-governance movement, aimed at reducing paper-based documentation and improving access to essential services. The integration of DigiLocker with Aadhaar, India's biometric identification system, facilitates seamless personal data management, enables users to verify their identity, access government records, and share important documents without physical copies (Kumar, 2019; Kumar et al., 2018) [1,2]. Despite its potential benefits, DigiLocker adoption rates vary, particularly in urban areas such as

Mangaluru City. Understanding the factors influencing users' intentions to adopt DigiLocker is crucial for optimising its utility across different demographic groups. A more thorough study of these characteristics within the framework of DigiLocker is necessary, even if earlier studies show that components like performance expectancy, effort expectancy, and facilitating conditions significantly influence the behavioural intention to use such services (Sivathanu, 2018). [3]. According to earlier research on digital platforms, the primary determinants of adoption include perceived usefulness (PU) and perceived ease of use (PEOU) (Davis, 1989) [4]. However, more research is necessary to comprehend the ways in which these traits interact with other elements, including self-efficacy and social influence (Saxena, 2018) [5]. Social influence, which speaks of the degree to which people believe that significant others believe They ought to make use of a new technology, contributes significantly to shaping behavioural intention, especially in collectivist cultures such as India. In such societies, family and community opinions can strongly influence personal decisions regarding the adoption of new technologies (Kaur et al., 2020; Shankar and Datta, 2018) [6,7]. Furthermore, self-efficacy which is the belief in one's own ability to use technology, significantly increases confidence and lowers the fear of using digital platforms. Both urban and rural consumers should consider this factor (Banu et al. 2019). [8]. Self-efficacy and intention to use e-governance technologies, such as DigiLocker, have been found to positively correlate in research, underscoring the significance of user confidence in encouraging broader adoption (Zaidi et al., 2021) [9]. The necessity for digital solutions has increased owing to the COVID-19 pandemic, which has highlighted the value of digital platforms for vital services and user perceptions of their usability and ease of adoption (Bagdi & Bulsara, 2023) [10]. Furthermore, as online transactions become more commonplace, addressing perceived risks such as data security and privacy has become essential for fostering trust and acceptance (Tiwari et al., 2021) [11]. The purpose of this study was to examine the variables shaping the Behavioural Intention to Use DigiLocker among residents of Mangaluru City. By examining how perceived usefulness, ease of use, social influence, and self-efficacy interact within the Technology Acceptance Model (TAM) framework, this research seeks to This study's objective was to investigate the dynamics driving DigiLocker adoption. This research enriches the scholarly discussion on technology acceptance and provides useful suggestions for decision-makers and digital service providers to boost user participation in e-governance initiatives. In essence, this study looks at how variables such as perceived utility, perceived user-friendliness, societal influence, and self-assurance affect users' intentions towards DigiLocker in Mangaluru. This investigation aims to uncover pragmatic solutions for policymakers to enhance DigiLocker's usability and accessibility, thereby supporting India's transition towards a more digitally inclusive society.

2. OBJECTIVES OF THE STUDY:

(1) To explore the factors influencing the Use of DigiLocker among Mangaluru users using an extended Technology Acceptance Model (TAM).
(2) To assess the impact of constructs such as perceived usefulness, perceived ease of use, social influence, and self-efficacy on the Behavioural Intention to Use DigiLocker.
(3) To identify the technical and contextual challenges affecting the Use of DigiLocker and to propose strategies to enhance user experience and trust.

3. LITERATURE REVIEW:

This literature review thoroughly analyzes key research on variables influencing technology adoption in areas like fintech services, e-learning, and mobile banking. These studies often use the Technology Acceptance Model and its extended versions, incorporating variables such as social influence (SI), self-efficacy (SE), and perceived value (PV). By examining perceived usefulness (PU), perceived ease of use (PEOU), and trust, the review identifies both domain-specific insights and common findings across technological contexts. Table 1 provides a detailed basis for understanding adoption dynamics across sectors, highlighting consistent predictors and cultural and technological nuances.

Table 1: Review of the Literature on the Main Elements Affecting the Adoption of Technology across Various Domains

Serial No.	Area	Focus of the Research	Results	Reference
1	Cloud-Based Payment Systems	TAM analysis of cloud-based payment systems	PU and PEOU consistently significant; new variables recommended for evolving technology landscape	(Mondego & Gide, 2022) [12]
2	Online Learning Intentions	Factors influencing digital natives' online learning	PU, PEOU, and SE significantly impact BIU	(Bagdi & Bulsara, 2023) [10]
3	SMS Advertising	Intention to receive SMS ads	PU and PEOU crucial for user intention; SEM validates relationships among TAM constructs	(Bamoriya & Singh, 2019) [13]
4	Social Networking Sites (SNS)	Intention to use SNS	PU, PEOU, and SI significantly influence BIU	(Dixit & Prakash, 2018) [14]
5	E-Learning During COVID-19	Cloud computing adoption in Indian universities	PU, PEOU impact BIU; external support factors influence acceptance	(Bhardwaj et al., 2021) [15]
6	E-Learning Among Undergraduates	E-learning adoption factors	PU and PEOU impact BIU, trustworthiness enhances usage	(Gupta & Thammi, 2021) [16]
7	Mobile Learning Adoption	Mobile technology adoption for learning	PU, PEOU significantly influence BIU, SE boosts student confidence	(Zaidi et al., 2021) [9]
8	Online Streaming Services	User adoption of streaming services	PU, PEOU critical; personality traits moderate technology acceptance	(Bhatt, 2021) [17]
9	Internet Banking	Internet banking adoption with service quality	PU, PEOU impact BIU; brand attitude mediates relationship	(Kaur & Malik, 2019) [18]
10	Luxury Consumer Behavior	Webrooming intentions among luxury consumers	PU, PEOU predict BIU; external influences shape behavior	(Jain & Shankar, 2021) [19]
11	E-CRM in Banking	Customer intention to use E-CRM in banking	PU, PEOU impact BIU, trust influences acceptance	(Mokha & Kumar, 2021) [20]
12	Mobile Banking	Mobile banking adoption in India	PU, PEOU significantly affect BIU; subjective norms and SE influence intentions	(Kumar et al., 2020) [21]
13	Blockchain in Supply Chains	Blockchain adoption among SMEs	PU, PEOU important for BIU; organizational factors also play a role	(Bhardwaj et al., 2021) [22]
14	Online Teaching	Impact of online teaching on BIU during COVID-19	PU, PEOU predict BIU; qualitative and quantitative methods validate findings	(Saleem et al., 2023) [23]

15	Electric Vehicles	Role of knowledge in EV adoption	PU, PEOU influence BIU, knowledge mediates adoption	(Jaiswal et al., 2021) [24]
16	Mobile Payment	Factors impacting mobile payment adoption	PU, PEOU critical for BIU; user-centric factors enhance adoption	(Shankar & Datta, 2018) [7]
17	E-Government Services	Acceptability of e-platform for peripartum care	PU, PEOU affect BIU; barriers to technology use need addressing	(Usmanova et al., 2020) [25]
18	Mobile Payment Platforms	Adoption of mobile payment platforms in Asia	PU, PEOU impact BIU, trust plays a crucial role	(Jawad et al., 2022) [26]
19	Big Data Analytics	Big data analytics usage and performance	PU, PEOU significantly influence satisfaction and continued use	(Gangwar, 2020) [27]
20	Mobile Banking	Adoption of mobile banking services	PU, PEOU influence BIU; CFA validates model	(Chawla & Joshi, 2019) [28]
21	E-Health	Continuance in e-health services	PU, PEOU affect BIU; ECM integration extends TAM applicability	(Kumar & Natarajan, 2020) [29]
22	Mobile Banking	Dual-phase mobile banking adoption model	PU, PEOU reduce resistance and increase adoption	(Rani & Mehta, 2018) [30]
23	Hospitality Industry	Enablers of Online Hotel Booking Intention (OHBI) in the Indian hospitality industry	Hotel website credibility and interactivity enhance PU, positively impacting OHBI. PEOU also boosts PU and OHBI. Service affordability strengthens PU’s effect on OHBI, while pandemic risk weakens it.	(Biswas, 2021) [31]
24	M-Health	Technology readiness in m-health acceptance	PU, PEOU impact BIU; readiness enhances acceptance	(Dash & Mohanty, 2023) [32]
25	Retail/Fashion	Antecedents of omni-channel shopping intention for fashion products among Indian millennials	PU strongly influences continuance intention to use omni-channel shopping, while PEOU shows no significant effect. Cost effectiveness and customer engagement positively impact continuance intention, ultimately affecting actual usage.	(Chaudhary et al., 2021) [33]
26	Online Banking	Relationship between TAM and customer satisfaction	PU, PEOU affect satisfaction and BIU	(Sathar et al., 2022) [34]
27	ATM Adoption	Multivendor ATM adoption model	PU, PEOU predict BIU; model extended with new variables	(Hota & Mishra, 2018) [35]
28	E-Recruitment	Gender differences in e-	PU, PEOU influence BIU; gender moderates’ relationships	(Kaur & Kaur, 2022) [36]

		recruitment adoption		
29	Luxury Purchase	Factors influencing online luxury purchase intentions	PU, PEOU predict BIU; social influence shapes behavior	(Jain, 2022) [37]
30	E-Learning	Acceptance of e-learning among higher ed students	PU, PEOU influence BIU; personal innovativeness enhances intentions	(Chahal & Rani, 2022) [38]

4. METHODOLOGY:

This study examines the elements that affect DigiLocker adoption among individuals in Mangaluru City, employing a methodical survey approach grounded in well-established theoretical models. The Technology Acceptance Model (TAM) forms the core framework, supplemented by additional components such as social influence (SI) and self-efficacy (SE), to offer a holistic view of user attitudes and adoption patterns. This study scrutinises crucial variables including perceived usefulness (PU), perceived ease of use (PEOU), Behavioural Intention to Use (BIU), and trust to capture the multifaceted aspects of technology acceptance. A meticulously crafted survey was developed to reflect the DigiLocker user experience in Mangaluru. This instrument integrates TAM-based metrics and extends them to encompass factors such as social influence (SI) and individual proficiency in technology use (SE). Using a Likert scale, the questionnaire assessed users' perceptions of DigiLocker's utility and user-friendliness as well as the influence of social networks and self-assurance on their inclination to use the platform. The sampling process ensured diverse representations across demographic groups, accounting for variations in age, sex, and educational background. Employing stratified random sampling, the study gathered responses from 200 DigiLocker users and individuals familiar with the platform's capabilities, ensuring that the results would encompass a broad-spectrum perspective within the community. To enhance accessibility, questionnaire was disseminated online and optimised for mobile devices. The distribution channels included local social media platforms and community networks to encourage participation across various segments of the Mangaluru population. The data collection phase lasted two months, allowing for a comprehensive accumulation of answers from individuals with different levels of digital experience. Before data analysis started, the sample's demographics were described using descriptive statistics. Using confirmatory factor analysis, the survey questions' ability to measure the components was confirmed. The associations between the TAM variables, SI, and SE were examined utilising structural equation modelling (SEM). The direct and indirect effects of PU, PEOU, SI, SE, and BI on DigiLocker were clarified by this path analysis, which also provided information on how strongly and in concert these factors influenced user adoption.

5. THEORETICAL BACKGROUND:

A fundamental framework for comprehending how people accept and plan to adopt new technologies is the Technology Acceptance Model (TAM). The TAM, which was first proposed by Davis (1989) [4], suggests that two important factors, perceived usefulness (PU) and perceived ease of use (PEOU), influence a person's propensity to accept technology. PU indicates how much a person thinks A particular system will enhance its performance, whereas PEOU indicates how easy it will be to use the system. These ideas have been carefully validated across diverse technological spheres, with research indicating that both PU and PEOU favourably associated with the Behavioural Intention to Use (King & Davis, 2000; King & He, 2006) [39, 40]. Recently, the TAM has been broadened to encompass additional constructs that capture contextual influences on technology adoption. Self-efficacy (SE) and social influence (SI) are included in this study to offer a deeper understanding of the variables influencing DigiLocker adoption among users in Mangaluru. SI, which is based on the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Theory of Planned Behaviour (TPB), illustrates how much individuals perceive that significant Others think they ought to utilise a specific technology (Ajzen, 1991; Venkatesh et al., 2003) [41, 42]. In a collectivist society like India, where community and family opinions hold considerable sway, SI is essential in moulding behavioural intentions. Previous studies have demonstrated that SI can be a potent determinant of technology adoption in such contexts, as users are often swayed by the views and actions of their social circles (Sivathanu, 2018; Kumar & Natarajan, 2020) [3, 29]. SE, another pertinent extension of TAM, represents an individual's conviction in its ability to execute a specific task (Bandura, 1986) [43]. In the realm of technology acceptance, SE refers to a user's confidence in their capacity to successfully employ a system. Research has shown that higher levels of SE are linked to increased intentions to adopt technology as users feel more competent and less anxious about using new systems (Shankar & Datta, 2018) [7]. SE is particularly relevant for DigiLocker adoption, as individuals with greater digital confidence are more likely to engage with digital document storage systems (Banu et al., 2019) [8]. Integrating these constructs within the TAM framework aligns with the broader findings that factors such as PU, PEOU, SI, and SE are significant predictors of technology adoption. In the context of DigiLocker, PU relates to the system's value in facilitating document storage and retrieval, whereas PEOU addresses the platform's user-friendliness. SI reflects the impact of peers and family members on users' intentions to adopt DigiLocker, and SE captures users' assurance in their capacity to use digital services effectively (Bagdi & Bulsara, 2023; Jawad et al., 2022) [10, 26].

6. PROPOSED RESEARCH FRAMEWORK:

The Technology Acceptance Model (TAM) has been expanded and is shown in the suggested study framework, which is illustrated in Figure 1. Other elements, including self-efficacy, social impact, and perceived value, were included in the improved model. This enlarged framework seeks to provide a more thorough comprehension of the factors influencing Mangaluru's adoption of DigiLocker. It suggests that five important constructs Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Social Influence (SI), Self-Efficacy (SE), and Perceived Value (PV) have an effect on the Behavioural Intention to Use (BIU) DigiLocker. Building on previous research in the field of technology adoption, this model examines the direct and indirect interactions between these variables.

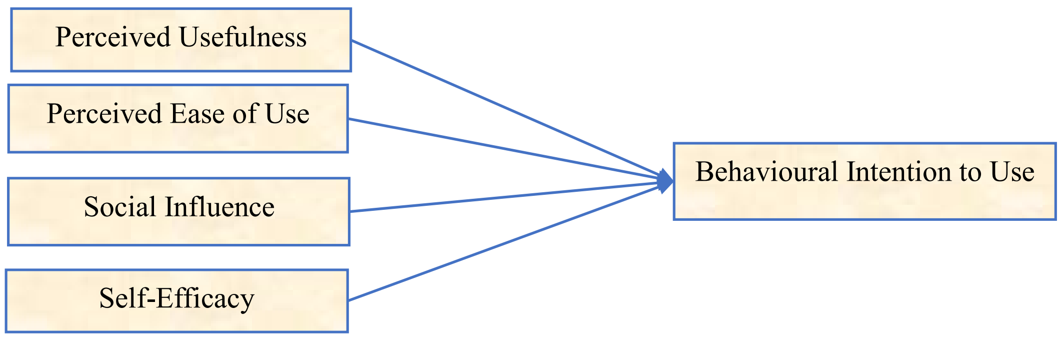

Figure 1: Proposed Research Framework

7. HYPOTHESES:

H1: Perceived Usefulness (PU) has a favourable impact on Behavioural Intention to Use (BIU).
H2: Perceived Ease of Use (PEOU) has a favourable impact on Behavioural Intention to Use (BIU).
H3: Self-efficacy (SE) has a favourable impact on Behavioural Intention to Use (BIU).
H4: Social Influence (SI) has a favourable impact on Behavioural Intention to Use (BIU).

8. RESULTS:

8.1 Demographic Profile and Descriptive Statistics

Table 2 presents a comprehensive breakdown of the respondents' demographic profiles, encompassing their age brackets, sex, educational attainment, professional status, and proficiency in digital technology. The sample exhibited a diverse distribution, with participants spanning various age categories, educational backgrounds, and occupational fields. The bulk of the respondents belong to the Generation Z and Millennial cohorts, with an equitable gender distribution and a significant proportion holding bachelor's or master's degrees. Furthermore, most participants reported an intermediate level of digital literacy, which aligns well with the study's emphasis on technological adoption. Table 3 provides an overview of the descriptive statistics for the main components used in the study, such as Behavioural Intention to Use (BIU), Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Social Influence (SI), and Self-Efficacy (SE). The matching mean, standard deviation, skewness, and kurtosis values for each construct are displayed. The skewness and kurtosis results support relative normalcy, and the overwhelmingly favourable mean scores for all items indicate favourable judgements. This response distribution suggests a generally favourable propensity for the technology to be adopted.

Table 2: Respondent's demographic profile

Variable	Description	Frequency	Percent
Age Group	Gen Z (1997–2012): 12–27 years old	91	45.5
	Millennials (1981–1996): 28–43	82	41.0
	Gen X (1965–1980): 44–59	27	13.5
	Total	**200**	**100.0**
Gender	Male	125	62.5
	Female	75	37.5
	Total	**200**	**100.0**
Education Level	High school or below	5	2.5
	PUC (Pre-University Course)	22	11.0
	Bachelor's degree	82	41.0
	Master's degree	67	33.5
	PhD / Professional degree	24	12.0
	Total	**200**	**100.0**
Occupation	Student	22	11.0
	Government employee	19	9.5
	Private sector employee	133	66.5
	Self-employed	12	6.0
	Unemployed	14	7.0
	Total	**200**	**100.0**
Digital Literacy	Beginner	27	13.5
	Intermediate	173	86.5
	Total	**200**	**100.0**

Source: Authors compilation based on the survey data

The respondents' demographic characteristics exhibited a well-balanced distribution across various factors, including age, gender, education, occupation, and digital literacy levels, contributing to the diversity of the sample. The age breakdown shows a predominance of younger individuals, with Gen Z (45.5%) and millennials (41%) comprising the majority. There was a notable male majority (62.5%. Educational attainment was high, with 86.5% of participants holding at least a bachelor's degree, while 66.5% worked in the private sector, suggesting potential familiarity with digital tools through work. Moreover, a considerable level of digital proficiency, with 86.5% classifying themselves as intermediate users, indicates general preparedness for digital platform adoption.

Table 3: Descriptive Statistics

Items	N	Mean	Std. Deviation	Skewness	Kurtosis
PU1	200	3.71	1.050	-1.040	.920
PU2	200	3.61	1.050	-.925	.695
PU3	200	3.64	1.085	-.829	.425

PEOU1	200	3.62	1.035	-.999	.899
PEOU2	200	3.65	1.073	-.902	.607
PEOU3	200	3.64	1.085	-.915	.576
SE1	200	3.68	.996	-.954	.932
SE2	200	3.69	1.010	-.899	.780
SE3	200	3.66	.968	-.928	.999
SI1	200	3.66	1.054	-.987	.818
SI2	200	3.59	1.024	-.970	.883
SI3	200	3.64	1.046	-1.002	.872
BI1	200	3.77	.868	-.828	1.427
BI2	200	3.86	.874	-1.000	1.781
BI3	200	3.85	.919	-1.255	2.214

Source: Authors work

The descriptive statistics revealed predominantly favourable attitudes across all measured constructs, with average scores ranging from 3.59 to 3.86 on a 5-point Likert scale. Items related to Perceived Usefulness (PU) and Behavioral Intention (BIU) exhibited higher mean scores (e.g. PU1 mean = 3.71, BI2 mean = 3.86), indicating a positive view of technology adoption. The range of the standard deviations was 0.835–1.085, suggesting a reasonable spread of responses without excessive variation (Sivathanu, 2018; Chahal & Rani, 2022) [3, 38]. The presence of negative skewness values (e.g. skewness for BI3 = -1.255) indicates a tendency towards higher responses, whereas kurtosis values (between 0.425 and 2.214) point to an approximately normal distribution. In behavioural sciences, skewness values within ±2 and kurtosis values within ±7 are typically deemed acceptable for normal distributions, thus supporting the validity and normality of the data (Byrne, 2016) [44]. This distribution aligns with the overall positive response trend, which is in line with earlier studies on the receptiveness of comparable demographics to technology adoption (Kumar and Natarajan 2020) [29].

8.2 Confirmatory Factor Analysis (CFA)

By investigating the relationships between observed variables (items) and their underlying latent constructs, such as Perceived Usefulness (PU), Perceived Ease of Use (PEOU), self-efficacy (SE), Social Influence (SI), and Behavioural Intention to Use (BIU), this study employed Confirmatory Factor Analysis (CFA) to authenticate the measurement model. Within this research context, CFA is essential in ensuring that each construct accurately reflects its corresponding items, thereby establishing construct validity and reliability. The rationale for employing CFA stems from the need to verify the structural integrity and theoretical underpinnings of the Technology Acceptance Model (TAM), as it pertains to DigiLocker adoption. CFA allows the researcher to corroborate that the hypothesised measurement model, encompassing latent variables such as PU and PEOU, corresponds to the gathered data. This process involves scrutinising key indicators, including factor loadings, composite reliability, and average variance extracted (AVE), to ascertain whether the items effectively capture the intended constructs (Byrne, 2016) [44]. Given the study's emphasis on comprehending the behavioural intention to use DigiLocker, a thorough validation of the measurement model through CFA is imperative. This ensures that the variables, as conceptualised, are accurately measured and suitable for subsequent structural equation modelling (SEM). This validation process enhances the robustness of the findings, bolstering their applicability in elucidating adoption behaviours in digital service contexts. Figure 2 illustrates the Confirmatory Factor Analysis model used for this purpose.

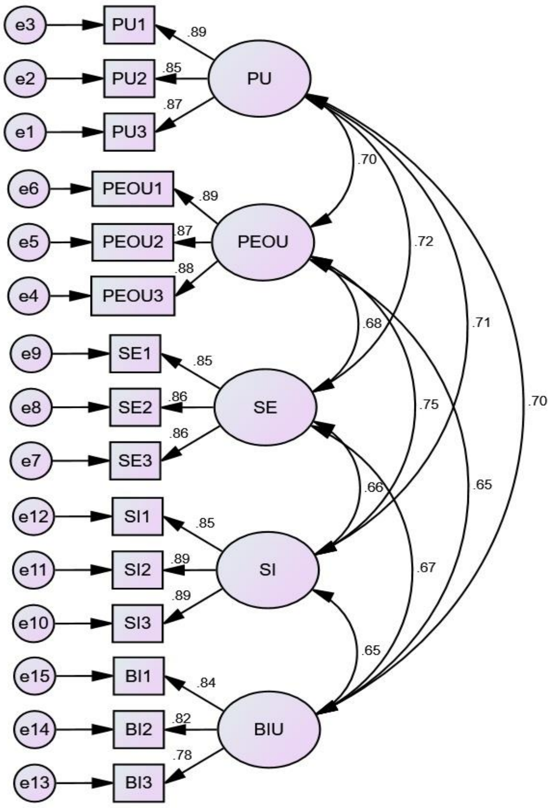

Figure 2: Confirmatory Factor Analysis Model

8.3 The goodness-of-fit indices of Confirmatory Factor Analysis Model

To assess the alignment of the measurement model with the observed data, various goodness-of-fit indices were examined. The CMIN/DF ratio of 1.138 fell well within the acceptable range of less than 3.0, indicating excellent model fit (Hair et al., 2019) [45]. Both CFI and IFI values were 0.995, exceeding the recommended threshold of 0.95ld, suggesting a strong correspondence between the model and data (Kline, 2023) [46]. The TLI value of 0.994 further corroborated the model's robust alignment with the observed data, as values above 0.95 are considered desirable (Wang & Wang, 2020) [47]. Furthermore, RMSEA was calculated to be 0.026, with a 90% confidence interval spanning from 0.000 to 0.049 and a PCLOSE value of 0.956. This signifies a close fit, as RMSEA values below 0.08 denote a reasonable fit, while those below 0.05 indicate a close fit and the NFI of 0.962 surpassed the 0.90 benchmark, providing additional support for the model's validity (Hair et al., 2019) [45]. Taken together, these indices demonstrate that the model fits the data well, confirming its appropriateness for analysis.

8.4 Evaluation of Measurement Model

Following best practices for confirmatory factor analysis, a comprehensive evaluation of the measurement model was conducted to guarantee the reliability and validity of the constructs employed in this investigation. Standardised factor loadings, Cronbach's Alpha, Composite Reliability (CR), Average Variance Extracted (AVE), and convergent and discriminant validity tests were among the most important metrics used in the evaluation. Cronbach's Alpha and CR values were employed to verify the constructs' reliability; both metrics exceeded the suggested 0.70 threshold, demonstrating excellent internal consistency among the items (Hair et al., 2019) [45]. Each concept effectively captured its intended variance, as evidenced by the AVE and CR measures, which showed convergent validity with AVE values over 0.50 and CR above AVE. By ensuring that the Maximum Shared Variance (MSV) was less than the AVE, and confirming that the constructs shared more variance with their own indicators than with other constructs, discriminant validity was demonstrated. Furthermore, discriminant validity was evaluated using the heterotrait–monotrait (HTMT) ratio. The constructs were empirically distinct when the HTMT values were less than 0.85, supporting the structural integrity of the model (Henseler et al., 2015) [48]. Each concept's validity and reliability metrics are listed in Table 4, which shows that every construct satisfies the required reliability and validity standards.

Table 4: Reliability and Validity of Model

Construct	Label	Standardized Factor Loading Values	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Perceived Usefulness	PU1	0.859	0.896	0.896	0.759
	PU2	0.873			
	PU3	0.853			
Perceived Ease of Use	PEOU1	0.866	0.906	0.907	0.913
	PEOU2	0.853			
	PEOU3	0.904			
Social Influence	SI1	0.876	0.912	0.912	0.891
	SI2	0.883			
	SI3	0.885			
Self-Efficacy	SE1	0.902	0.917	0.917	0.787
	SE2	0.889			
	SE3	0.869			
Perceived Value	PV1	0.904	0.917	0.918	0.788
	PV2	0.884			
	PV3	0.875			
Behavioural Intention to Use	BIU1	0.832	0.859	0.859	0.671
	BIU2	0.820			
	BIU3	0.805			

Source: Authors work

8.5 Test of Convergent validity and Discriminant Validity

Tests of discriminant and convergent validity were employed to assess the measurement model and confirm the reliability and validity of the constructs used in this investigation. Convergent validity was evaluated to ensure that each construct's items accurately reflected their intended latent components and were sufficiently associated. This was achieved by examining important metrics such as Average Variance Extracted (AVE) and Composite Reliability (CR). CR values exceeding 0.70 and AVE values exceeding 0.50 for every construct showed adequate internal consistency and significant variance capture by the constructs, verifying that the constructs successfully measured the intended concepts and supported their convergent validity (Hair et al., 2019) [45]. Discriminant validity, however, guarantees that every construct is unique and does not have an undue correlation with other constructs. The Maximum Shared Variance (MSV), which ought must be lower than the AVE for each component, was accustomed to assess the discriminant validity. Additionally, the constructs' empirical distinctiveness was confirmed by the use of the Heterotrait-Monotrait (HTMT) ratio as an additional measure, with values below 0.85 (Henseler et al., 2015) [48]. The discriminant validity of the model was further supported by the HTMT analysis, which revealed minimal overlap between the constructs. The discriminant validity analysis with CR, AVE, MSV, and intercorrelations between the constructs is shown in Table 5. The HTMT ratios between the constructs are displayed in Table 6, which supports the idea that each construct retains empirical differentiation.

Table 5: Discriminant Validity Analysis

	CR	AVE	MSV	MaxR(H)	PU	PEOU	SE	SI	BIU
PU	0.904	0.759	0.516	0.906	0.871				
PEOU	0.913	0.777	0.567	0.913	0.698*	0.882			
SE	0.891	0.732	0.516	0.891	0.718*	0.682*	0.855		
SI	0.907	0.765	0.567	0.909	0.706*	0.753*	0.660*	0.875	
BIU	0.857	0.666	0.486	0.860	0.697*	0.654*	0.670*	0.653*	0.816

Source: Authors work

Table 6: HTMT Analysis

	PU	PEOU	SE	SI	BIU
PU					
PEOU	0.701				
SE	0.724	0.684			
SI	0.711	0.752	0.663		
BIU	0.696	0.654	0.672	0.654	

Source: Authors work

8.6 Structural Equation Modelling (SEM) Analysis

Structural Equation Modelling, was used here to investigate the connections between constructs and validate the suggested research model. Researchers can simultaneously examine the measurement model (the relationship between observed indicators and their underlying latent constructs) and structural model at the same time using SEM, a reliable method of statistics that blends factor analysis and multiple regression analysis (Hair et al., 2019) [45]. This dual functionality renders SEM particularly appropriate for investigations aimed at exploring the intricate relationships between constructs and validating theoretical models. A thorough evaluation of how these factors interact and impact one another in the context of technology adoption is made possible by SEM, given the theoretical framework of this study, which includes constructs such as Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Social Influence (SI), self-efficacy (SE), and behavioural intention to use (BIU). Using SEM, this research seeks to verify whether the hypothesised paths between these constructs are valid and to quantify the strength of these relationships. The SPSS AMOS program was utilised for the analysis, which revealed information about the model's fit, as well as the importance and direction of the links between the constructs. The results derived from SEM validate the relevance of the Technology Acceptance Model (TAM) and its extensions in the context of digital technology adoption and provide a deeper understanding of the elements influencing behavioural intention to use in this study. The Structural Path Analysis Model used to assess these linkages is shown in Figure 3.

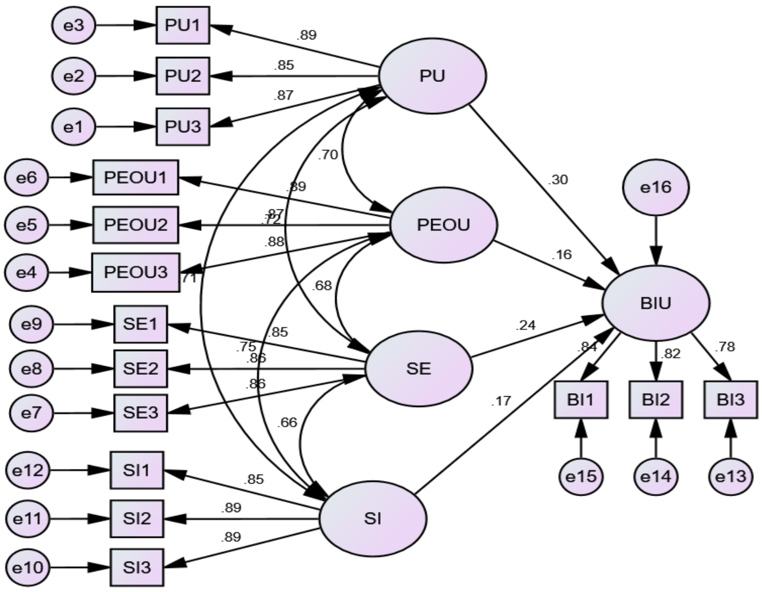

Figure 3: Structural Path Analysis Model

8.7 The goodness-of-fit indices of Structural Path Analysis Model

Various important criteria were utilised to assess model fit. An outstanding match was suggested by the CMIN/DF ratio of 1.138, which was well within the permissible range of below 3.0. A robust match was shown with scores of 0.995 for both CFI and IFI, which were over the 0.95 threshold. Given that values more than 0.95 are regarded as beneficial, the TLI value of 0.994 further supports the model's good alignment. With a 90% confidence interval (CI) between 0.000 and 0.049, the computed RMSEA was 0.026, suggesting a close fit. The model's strength was further demonstrated by an NFI value of 0.962, which is above the benchmark of 0.90. All these indicators indicate a satisfactory fit between the measurement model and data (Hair et al., 2019) [45].

8.8 Hypothesis Testing

This study's hypothesis testing offers important new information on the connections between behavioural intention to use (BIU) and its main variables, social influence (SI), perceived usefulness (PU), perceived ease of use (PEOU), and self-efficacy (SE). Each hypothesis examines the role of these constructs within the Technology Acceptance Model (TAM) framework, focusing on how these elements work together to affect users' intentions to adopt the technology under study. By analysing standardised regression weights (β), along with associated statistical metrics such as critical ratios (C.R.) and p-values, this test seeks to validate the hypothesised paths and quantify the power of each relationship. This approach allows for a thorough comprehension of the influences of PU, PEOU, SE, and SI on BIU, providing empirical evidence to support or refute each hypothesis. These results provide a deeper understanding of digital adoption behaviour, particularly under the framework of the constructs integrated within the TAM framework, thus advancing theoretical and practical information about the elements that encourage technology adoption. Table 7 presents the results of the hypothesis test, offering a detailed view of these relationships.

Table 7: Results of the Hypothesis Test

Hypothesis		Hypothesized Relationship	Standardized Regression Weight (β)	Standard Error (S.E.)	Critical Ratio (C.R.)	p-value	Decision on Hypothesis
H1		BIU <--- PU	0.298	0.08	3.72	0.0002	Accepted
H2		BIU <--- PEOU	0.157	0.08	1.96	0.0498	Accepted
H3		BIU <--- SE	0.238	0.086	2.77	0.0056	Accepted
H4		BIU <--- SI	0.168	0.081	2.07	0.0385	Accepted

Source: Authors work

The outcomes of hypothesis testing provide important information about the relationships between behavioural intention to use (BIU) and its predictors, which include social influence (SI), perceived usefulness (PU), perceived ease of use (PEOU), and self-efficacy (SE). Standardised regression weights (β) demonstrate the strength of these connections, while p-values and critical ratios (C.R.) verify statistical significance for all variables. There is strong evidence for H1, which looks at the relationship between PU and BIU, with β = 0.298, C.R. = 3.72, and p-value = 0.0002. This suggests that the intention to use technology is positively impacted by higher perceived utility. H2, investigating PEOU and BIU, showed marginal significance, with β = 0.157, C.R. = 1.96, and p-value = 0.0498. While ease of use positively influences behavioural intention, its impact is less pronounced than that of other factors. H3, exploring SE and BIU, demonstrated a notable significance with β = 0.238, C.R. = 2.77, p = 0.0056), supporting the notion that self-efficacy significantly influences intention to use the system. Finally, H4, examining SI and BIU, revealed a significant relationship with β = 0.168, C.R. = 2.07, and p-value = 0.0385, suggesting that social influence also positively affects usage intention.

9. DISCUSSION:

The findings are interpreted in the discussion section, which explores how each construct influences the intention to utilise DigiLocker as per the Technology Acceptance Model (TAM). This analysis was carried out inside the framework of the study's aims, examining the importance of the findings in relation to behavioural intentions.

9.1 Perceived Usefulness (PU)

According to the results, perceived usefulness (PU) serves as a key factor influencing Behavioral Intention (BIU) to utilise DigiLocker, which aligns with the fundamental principle of TAM that perceived advantages drive user adoption. Studies on digital services consistently demonstrate that perceived utility contributes significantly to technology acceptance as users prioritise functional benefits (Mondego & Gide, 2022; Kumar et al., 2020) [12, 21]. In the case of DigiLocker, the advantages of convenience and security appear to be crucial for promoting adoption, highlighting the need to effectively communicate these benefits to enhance uptake.

9.2 Perceived Ease of Use (PEOU)

Although Perceived Ease of Use (PEOU) has a favourable impact on Behavioural Intention to Use (BIU), its influence is not as strong as Perceived Usefulness (PU). This suggests that, even though consumers appreciate a user-friendly interface, the functionality of DigiLocker plays a more crucial role in adoption decisions. Similar outcomes have been observed in research on technology acceptance, where PEOU enhances user experience but is not always the primary factor driving adoption (Dixit & Prakash, 2018; Mondego & Gide, 2022) [14, 12]. These results imply that tactics for promoting DigiLocker's adoption may be more efficient if they emphasise its real-world uses as opposed to solely focusing on its ease of use.

9.3 Self-Efficacy (SE)

Self-efficacy (SE) is essential in influencing Behavioural Intention to Use (BIU), implying that people who are confident in their digital abilities are more inclined to embrace DigiLocker. This finding is consistent with research on digital platforms that demonstrate a strong link between self-efficacy and the likelihood of adopting new technologies (Bagdi & Bulsara, 2021; Bagdi & Bulsara, 2023) [9, 10]. To promote wider acceptance, DigiLocker can offer learning resources, such as instructional guides, aimed at enhancing users' self-assurance and digital competence.

9.4 Social Influence (SI)

The impact of Social Influence (SI) on Behavioural Intention to Use (BIU) is statistically significant, albeit moderate, suggesting that whilst community perspectives are relevant, they are less influential than individuals' personal convictions and self-assurance in utilising DigiLocker. Research on technology adoption in comparable contexts has demonstrated that social influence can shape adoption choices, although its effect may fluctuate in urban environments (Bagdi and Malik, 2019; Bagdi and Bulsara, 2023) [18, 10]. This implies that DigiLocker adoption in Mangaluru may be predominantly driven by individual factors, with users placing greater focus on their personal assessments as opposed to seeking social approval.

9.5 Theoretical Implications

The Technology Acceptance Model (TAM) is enhanced by this study by confirming its constructs in the realm of DigiLocker adoption within an Indian urban setting. The significant impact of Perceived Usefulness (PU) reinforces the TAM's focus on perceived benefits as a key factor in user acceptance. Nevertheless, the limited role of Social Influence (SI) indicates that TAM might benefit from refinement to account for contextual differences in social dynamics, especially in urban areas where individual judgements may be more influential (Mondego & Gide, 2022) [12]. This observation suggests that the TAM can be adjusted to better reflect the unique aspects of technology adoption in urban environments.

9.6 Practical Implications

The results offer practical advice for improving DigiLocker uptake. Authorities and platform developers should prioritise highlighting the system's practical advantages, including ease of use, data protection, and remote access, as these elements could stimulate adoption. Studies indicate that effectively conveying functional benefits drives user acceptance in comparable scenarios (Bhardwaj et al., 2021) [16]. Moreover, offering support materials, such as instructional guides, might boost users' self-efficacy (SE) in navigating the platform, thereby addressing a crucial adoption factor. Given the lesser impact of social influence (SI), promotional tactics may be better directed towards meeting individual user requirements.

9.7 Limitations and Future Research Directions

This study's focus on an urban area in Mangaluru may hinder the relevance of its results to rural or culturally diverse regions. Future studies could address this by encompassing rural populations or additional urban centres, examining how geographical and cultural factors influence DigiLocker adoption. Moreover, the cross-sectional nature of this research hinders understanding of long-term adoption patterns. Longitudinal investigations can offer a more comprehensive understanding of sustained usage over time. The minimal impact of SI warrants further exploration of how social dynamics affect technology adoption in various cultural contexts. Future research could also look into additional factors, such as perceived trust and privacy issues, which may have an impact adoption in scenarios involving personal data management.

10. CONCLUSION:

This research underscores the importance of elements like Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Self-Efficacy (SE), and Social Influence (SI) in shaping urban Indian users' Behavioural Intention to Use (BIU) DigiLocker. The substantial impact of PU indicates that users are primarily driven by practical advantages, confirming the fundamental principle of the Technology Acceptance Model (TAM). The notable yet comparatively modest role of PEOU suggests that, while user-friendliness is appreciated, it is less influential than the perceived utility of the platform. Likewise, the relevance of SE implies that users' faith in their capacity to effectively utilise DigiLocker enhances their likelihood of adoption. Notably, the study revealed that SI, a crucial factor in collectivist societies, had a relatively minor influence on BIU. This divergence suggests that urban Indian users may prioritise individual benefits and pragmatic considerations over social endorsements when adopting government-provided digital services. This result suggests that although the TAM's social influence component is valuable, its impact may fluctuate based on context and user demographics, particularly in urban settings. From a practical standpoint, this study emphasises the need for DigiLocker developers and government bodies to draw attention to the platform's security, convenience, and utility in their user engagement efforts. Educating users and offering support to boost self-efficacy could foster a more favourable adoption environment. This approach aligns with the findings of the study that users are more responsive to individual-centred benefits rather than social persuasion. Future investigations could expand on these results by incorporating broader samples from rural and diverse urban areas, examining long-term adoption trends, and exploring other relevant factors, such as trust and privacy. This research contributes to the ongoing discourse on digital platform adoption by providing information that can help policymakers and developers in enhancing technology acceptance and promoting a digitally inclusive society.

REFERENCES:

[1] Kumar, R. (2019). Digilocker (digital locker – a better India for tomorrow). *International Journal of Advanced Research, 7*(6), 630-638. https://doi.org/10.21474/ijar01/9265

[2] Kumar, V., Chaturvedi, A., Dave, M. (2018). A solution to secure personal data when Aadhaar is linked with DigiLocker. *International Journal of Computer Network and Information Security, 10*(5), 37-44. https://doi.org/10.5815/ijcnis.2018.05.05

[3] Sivathanu, B. (2018). An empirical study of cloud-based e-governance services adoption in India. *International Journal of Electronic Government Research, 14*(1), 86-107. https://doi.org/10.4018/ijegr.2018010105

[4] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008

[5] Saxena, S. (2018). Role of "perceived risks" in adopting mobile government (m-government) services in India. *Foresight, 20*(2), 190-205. https://doi.org/10.1108/fs-08-2017-0040

[6] Kaur, J., Kaur, S., Syan, A., & Sharma, R. (2020). Factors influencing the adoption of payment banks in India using an extended TAM. *Asia-Pacific Journal of Management Research and Innovation, 16*(4), 309-321. https://doi.org/10.1177/2319510x211013598

[7] Shankar, A., & Datta, B. (2018). Factors Affecting Mobile Payment Adoption Intention: An Indian Perspective. *Global Business Review,* 19(3_suppl), S72-S89. https://doi.org/10.1177/0972150918757870

[8] Banu, A., Mohamed, N., Parayitam, S. (2019). Online banking and customer satisfaction: Evidence from India. *Asia-Pacific Journal of Management Research and Innovation, 15*(1-2), 68-80. https://doi.org/10.1177/2319510x19849730

[9] Zaidi, S., Osmanaj, V., Ali, O., Zaidi, S. (2021). Adoption of mobile technology for mobile learning by university students during COVID-19. *International Journal of Information and Learning Technology, 38*(4), 329-343. https://doi.org/10.1108/ijilt-02-2021-0033

[10] Bagdi, H. & Bulsara, H. (2023). Understanding the role of perceived enjoyment, self-efficacy, and system accessibility: Digital natives' online learning intentions. *Journal of Applied Research in Higher Education, 15*(5), 1618-1631. https://doi.org/10.1108/jarhe-09-2022-0302

[11] Tiwari, P., Tiwari, S., Gupta, A. (2021). Examining the impact of customers' awareness, risk, and trust in m-banking adoption. *FIIB Business Review, 10*(4), 413-423. https://doi.org/10.1177/23197145211019924

[12] Mondego, D. and Gide, E. (2022). The use of the Technology Acceptance Model to analyse the Cloud-Based Payment Systems: A Comprehensive Review of the Literature. *Journal of Information Systems and Technology Management*, 19(1), 1-30. https://doi.org/10.4301/s1807-1775202219007

[13] Bamoriya, H., and Singh, R. (2019). SMS advertising in India: Is TAM a robust model for explaining intention? *Organizations and Markets in Emerging Economies*, 3(1), 89-101. https://doi.org/10.15388/omee.2012.3.1.14277

[14] Dixit, R. and Prakash, G. (2018). Intentions to use social networking sites (SNS) using Technology Acceptance Model (TAM). *Paradigm: A Management Research Journal*, 22(1), 65-79. https://doi.org/10.1177/0971890718758201

[15] Bhardwaj, A., Garg, L., Garg, A., Gajpal, Y. (2021). E-learning during COVID-19 outbreak: Cloud computing adoption in Indian public universities. *Computers, Materials & Continua*, 66(3), 2471-2492. https://doi.org/10.32604/cmc.2021.014099

[16] Gupta, M. and Thammi, S. (2021). A study of the application of Technology Acceptance Model (TAM) to e-learning among undergraduate students in India: A structural equation modelling approach. *Asian Journal of Management*, 12(3), 243-252. https://doi.org/10.52711/2321-5763.2021.00037

[17] Bhatt, K. (2021). Adoption of online streaming services: Moderating role of personality traits. *International Journal of Retail & Distribution Management*, 50(4), 437-457. https://doi.org/10.1108/ijrdm-08-2020-0310

[18] Kaur, A. and Malik, G. (2019). Examining factors influencing Indian customers' intentions and adoption of internet banking: Extending TAM with electronic service quality. *Innovative Marketing*, 15(2), 42-57. https://doi.org/10.21511/im.15(2).2019.04

[19] Jain, S. and Shankar, A. (2021). Exploring Gen Y luxury consumers' webrooming behavior: An integrated approach. *Australasian Marketing Journal (AMJ)*, 30(4), 371-380. https://doi.org/10.1177/18393349211022046

[20] Mokha, A., and Kumar, P. (2021). Using the Technology Acceptance Model (TAM) in understanding customers' Behavioural Intention to Use e-CRM: Evidence from the banking industry. *Vision: The Journal of Business Perspective*. 25(4), https://doi.org/10.1177/09722629211060565

[21] Kumar, A., Dhingra, S., Batra, V., & Purohit, H. (2020). A framework of mobile banking adoption in India. *Journal of Open Innovation Technology Market and Complexity*, 6(2), 1-17. https://doi.org/10.3390/joitmc6020040

[22] Bhardwaj, A., Garg, A. and Gajpal, Y. (2021). Determinants of blockchain technology adoption in supply chains by SMEs in India. *Mathematical Problems in Engineering*, 2021, 1-14. https://doi.org/10.1155/2021/5537395

[23] Saleem, I., Shamsi, M., & Magd, H. (2023). Impact assessment of ease and usefulness of online teaching in higher education in post-COVID era. *International Journal of Information and Education Technology*, 13(1), 102-113. https://doi.org/10.18178/ijiet.2023.13.1.1785

[24] Jaiswal, D., Kant, R., Singh, P., & Yadav, R. (2021). Investigating the role of electric vehicle knowledge in consumer adoption: Evidence from an emerging market. *Benchmarking: An International Journal*, 29(3), 1027-1045. https://doi.org/10.1108/bij-11-2020-0579

[25] Usmanova, G., Gresh, A., Cohen, M. A., Kim, Y.-M., Srivastava, A., Joshi, C. S., Bhatt, D. C., Haws, R., Wadhwa, R., Sridhar, P., & others. (2020). Acceptability and barriers to use of the ASMAN provider-facing electronic platform for peripartum care in public facilities in Madhya Pradesh and Rajasthan, India: A qualitative study using the Technology Acceptance Model-3. *International Journal of Environmental Research and Public Health, 17*, Article 8333. https://doi.org/10.3390/ijerph17228333

[26] Jawad, A., Parvin, T., & Hosain, S. (2022). Intention to adopt mobile-based online payment platforms in three Asian countries: An application of the extended Technology Acceptance Model. *Journal of Contemporary Marketing Science*, 5(1), 92-113. https://doi.org/10.1108/jcmars-08-2021-0030

[27] Gangwar, H. (2020). Big data analytics usage and business performance: Integrating the Technology Acceptance Model (TAM) and Task Technology Fit (TTF) Model. *Electronic Journal of Information Systems Evaluation*, 23(1), 45-64. https://doi.org/10.34190/ejise.20.23.1.004

[28] Chawla, D., and Joshi, H. (2019). Scale development and validation for measuring the adoption of mobile banking services. *Global Business Review*, 20(2), 434-457. https://doi.org/10.1177/0972150918825205

[29] Kumar, K., Natarajan, S. (2020). An extension of the Expectation Confirmation Model (ECM) to study continuance behavior in using e-health services. *Innovative Marketing*, 16(2), 15-28. https://doi.org/10.21511/im.16(2).2020.02

[30] Rani, A. and Mehta, K. (2018). A study on development of dual phase mobile banking adoption model. *Journal of Technology Management for Growing Economies*, 9(2), 171-197. https://doi.org/10.15415/jtmge.2018.92004

[31] Biswas, A. (2021). Reconnoitering enablers of travelers' online hotel booking intention: moderation of service affordability and perceived pandemic risk. International Journal of Quality & Reliability Management, 40(2), 542-565. https://doi.org/10.1108/ijqrm-10-2021-0363

[32] Dash, A. and Mohanty, S. (2023). Technology readiness and the older citizen's acceptance of m-health services in India. *Digital Policy Regulation and Governance*, 25(2), 169-183. https://doi.org/10.1108/dprg-11-2022-0126

[33] Chaudhary, P., Singh, A., Sharma, S. (2021). Understanding the antecedents of omni-channel shopping by customers with reference to fashion category: the indian millennials' perspective. Young Consumers Insight and Ideas for Responsible Marketers, 23(2), 304-320. https://doi.org/10.1108/yc-05-2021-1327

[34] Sathar, M., Rajagopalan, M., Naina, S., Parayitam, S. (2022). A moderated-mediation model of perceived enjoyment, security and trust on customer satisfaction: Evidence from banking industry in India. *Journal of Asia Business Studies*, 17(3), 656-679. https://doi.org/10.1108/jabs-03-2022-0089

[35] Hota, J., and Mishra, S. (2018). Development and validation of a multivendor ATM adoption model in India. *The International Journal of Bank Marketing*, 36(5), 884-907. https://doi.org/10.1108/ijbm-02-2017-0035

[36] Kaur, D. and Kaur, R. (2022). Elucidating the role of gender differences via TAM in e-recruitment adoption in India: A multi-group analysis using MICOM. *The Bottom Line Managing Library Finances*, 35(2/3), 115-136. https://doi.org/10.1108/bl-11-2021-0104

[37] Jain, S. (2022). Factors influencing online luxury purchase intentions: The moderating role of bandwagon luxury consumption behavior. *South Asian Journal of Business Studies*, 13(1), 90-117. https://doi.org/10.1108/sajbs-09-2021-0352

[38] Chahal, J. & Rani, N. (2022). Exploring the acceptance for e-learning among higher education students in India: Combining technology acceptance model with external variables. *Journal of Computing in Higher Education, 34*(3), 844-867. https://doi.org/10.1007/s12528-022-09327-0

[39] Venkatesh, V. and Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

[40] King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management*, *43*(6), 740–755. https://doi.org/10.1016/j.im.2006.05.003

[41] Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

[42] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Towards a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

[43] Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Sage Publications Ltd, pages 1-373 Google Scholar

[44] Byrne, B. M. (2016). *Structural equation modelling with AMOS: Basic concepts, applications, and programming* (3rd ed.). Routledge, pages 1-460. https://doi.org/10.4324/9781315757421

[45] Hair J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate Data Analysis*, 8/e, Cengage Learning, pages 1-813 Google Scholar

[46] Kline, R. B. (2023). *Principles and practice of structural equation modelling* (5th ed.). Guilford Press, pages 1-425. Google Scholar

[47] Wang, J., & Wang, X. (2020). *Structural equation modelling: Applications using Mplus* (2nd ed.). Wiley, pages 1-536 Google Scholar

[48] Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modelling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8