International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Fintech And Digital Transformation of the Banking and Finance Industry. A Study on Major Trends and Adaption by Consumer and Implications for the Existing Industry Stakeholders in Gujarat

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ABSTRACT:

This research explores the evolution and impact of Digital Payment Methods (DPMs) in Gujarat. It analyzes consumer adoption of DPMs and Digital banking factors contributing to the rapid ascent in the usage of these services. The research also provides a comprehensive overview of the Fintech Market globally. It highlights role of Fintech companies in reshaping traditional financial services. Aiming to provide nuanced understanding of the challenges and opportunities associated with DPMs, it outlines the barriers influencing customer adoption like privacy concern, security risk, access issue and impersonalization factor are scrutinized in detail. Additionally, study accesses the impact of trust, ease-to-use, usefulness and social factor.

KEYWORDS: Digital Payment Methods, Fintech, Consumer adoption, Banking, Barrier.

INTRODUCTION:

The utilization of technology, especially within the financial sector, has ushered in significant transformations and opportunities. Fintech companies, offering alternatives to conventional banking, have brought forth innovative solutions, contributing to heightened economic prosperity and stability (Skan, Dickerson, & Masood, 2015). The journey towards a cashless society has been hastened by the emergence of digital payment channels like internet banking and mobile banking (Jiménez and Díaz, 2019). The COVID-19 pandemic has further underscored the importance of digital payment mechanisms (Chen et al., 2020).

Sweden, recognized for its advanced technological infrastructure, presents an intriguing case for studying the widespread adoption of digital payment methods (Thomas et al., 2016). Nevertheless, the transition to a cashless society is not devoid of challenges, notably pertaining to privacy apprehensions (Larsson et al., 2016). Grasping the impediments and advantages of full adoption is pivotal (Moriuchi, 2021), with research indicating that factors like user-friendliness and social influence play pivotal roles in bolstering adoption intentions (Lee, 2009; Tan and Leby Lau, 2016).

Furthermore, it's imperative to discern between different segments of adopters, such as adopters-accepters (AAs) and adopters-resisters (ARs), given their differing attitudes and behaviors (Planing, 2014). Young bank customers (YBCs) hold particular significance due to their propensity for rapid technology adoption (Tan and Leby Lau, 2016). Additionally, delving into the perspectives of customers who resist innovations, exemplified by groups like Kontantupproret in Sweden, offers valuable insights (Arvidsson et al., 2017).

In summary, this thesis endeavors to explore the inclination towards fully embracing digital payment methods, taking into account both the obstacles and enablers, while examining various segments of bank customers in Sweden.

1. DIGITAL PAYMENT METHODS

Digital payments have evolved over the last 20 years which slowly started gaining traction from users and researchers as it was bringing about a change in modern e-commerce. As it was gaining traction, researchers started defining it in different ways, focusing on different areas such as business, IT, accounts and finance. According to Briggs and Brooks (2011) digital payment is a form of payment that is supported by banks and is connected between individuals and banks to perform monetary transactions digitally. Peter and Babatunde (2012) viewed digital payment as a way of making payments, transactions or money transfers with the help of the internet. In the same context, Adeoti and Osotimehin (2012) referred to digital payment as a way of making payment online or at a particular location using digital medium. Kaur and Pathak (2015) suggested that digital payments are those payments which are made for e-commerce purpose where money is exchanged through digital mode. Based on the above definition we can conclude that digital payment is a method of payment that involves various digital platforms or applications to conduct transactions using digital mediums.

2. CONSUMER ADOPTION OF DPMs

Consumer acceptance of DPM has increased in recent years due to factors such as ease of access to DPM services and attractive fees and interest rates offered by DPM companies. Important patterns in consumer DPM adoption include. The rise of mobile banking and digital wallets has been remarkable, driven by their convenient and simple ways to manage finances and conduct transactions, which has resonated well with consumers. Progress driven by DPM in promoting financial inclusion includes the expansion of financial services to previously marginalized groups, such as those facing financial difficulties and individuals without access to traditional banking services. Data confirms this pattern, as a recent Deloitte study reported that 70% of consumers are now using at least one product or service offered by a DPM. Additionally, an increasing proportion of consumers are adopting mobile banking apps as a primary way to handle their finances.

3. FACTORS INFLUENCING CONSUMER INTENTION TO ADOPT DPMs: BALANCING BARRIER AND ENABLERS.

- Privacy concern regarding the protection of personal information may deter individuals from adopting DPMs.
- Security risks of transaction and potential fraud or hacking incidents can acts as barrier.
- Limited access issues to digital infrastructure such as internet connectivity or smartphones may hinder individuals.
- Lack of personalized interactions in digital transaction may create reluctance among consumer.
- Lack of trust and confidence in the reliability and integrity of DPMs system and providers may impede adoption
- Ease-to-use interfaces that simplify the process of DPMs can encourage adoption to overcome complexities
- Social influence can motivate individuals to adopt fintech methods
- Convenience and efficiency benefits and practical advantages can motivate adoption by demonstrating their usefulness.
- Establishment of credibility through positive user experience and transparent policies can encourage customers.

RESEARCH OBJECTIVES:

1. To examine the relationship between demographic factors of consumer and various barriers such as privacy barriers, security barriers, access barriers, impersonalization barriers, and trust barriers.
2. To examine the relationship between the demographic factor of consumers and various barrier-breakers like ease-to-use barrier-breakers. Social-influence barrier-breaker, usefulness barrier-breaker, credibility barrier-breaker
3. To examine the relationship between intention to fully adopt DPMs in the future and its association with demographic factor.

LITERATURE REVIEW:

1. **Teshome and Sharma (2023)** conducted a review focusing on the adoption of fintech technology by bank customers. They critically analyzed previous studies that employed models like the Theory of Reasoned Action, Technology Acceptance Model, and Unified theory of acceptance and use of technology to examine the adoption of financial technology in the banking sector. The review found that these constructs significantly influenced the behavioral intention of bank customers to adopt and use financial technology applications.
2. **Slazus & Bick, (2022)** A consumer behavioural study analysed FinTech adoption in South Africa using a mixed-methods approach. Six influencing factors were identified: Utility, Socio-Economic Influencers, Mobile Device Trust, Youth, Perceived Risks and Associated Costs. Interestingly, 74% of respondents indicated that they would join a completely branchless bank. An Enhancement Criteria Model is proposed to improve FinTech business models.
3. **Barroso and Laborda (2022)** conduct a systematic literature review on digital transformation and the emergence of the FinTech sector. Through a comprehensive review of existing literature, the authors likely provide a synthesized understanding of how digital transformation dynamics, technological advancements, and regulatory changes have collectively contributed to the rise of FinTech. This work serves as a valuable resource for scholars, practitioners, and policymakers seeking to comprehend the multifaceted interactions between digital transformation and FinTech evolution.
4. **Hasan, R., Ashfaq, M., & Shao, L. (2021).** "Evaluating Drivers of Fintech Adoption in the Netherlands." This study investigates factors influencing Dutch customers' adoption of mobile payments, highlighting the significance of perceived ease of use, usefulness, safety, and trust. It also underscores the impact of COVID-19 in reducing cash payments and increasing contactless payments as mobile payments contribute to public health and virus containment.
5. **Kiranga, I., & Chotiyaputta, V. (2021).** This study critically reviews previous research on the adoption of financial technology in the banking sector, with a particular focus on bank customers. It highlights the influence of constructs from theories like the Theory of Reasoned Action,

the Technology Acceptance Model, and the Unified theory of acceptance and use of technology on customers' behavioral intention to adopt and use financial technology applications

6. **Setiawan et.al (2021)** This research highlights the pivotal role of Fintech in expanding financial access to unbanked populations in rural Indonesia. User innovativeness and attitude were significant predictors of Fintech adoption, while financial literacy played a less important role. To enhance inclusivity, the government should improve ICT infrastructure and support Fintech startups and innovation in collaboration with traditional financial institutions.
7. **Lien, Doan, and Bui (2020)** and her team studied DPMs application in Vietnam's banking sector, surveying 620 Ho Chi Minh City bank customers. Their research identified factors like perceived usefulness, social impact, customer trust, and ease of use that positively influence customer intention to use DPM services, providing crucial insights for improving service quality and informing strategic decisions for bank managers, policymakers, and researchers.
8. **Khatun, N., & Tamanna, M. (2020).** This survey in Bangladesh investigates factors affecting Fintech adoption in financial institutions using the UTAUT model and eight key factors. Based on data from 265 employees, the study reveals that effort expectancy, social influence, facilitating conditions, perceived reliability, and added value positively influence the intention to adopt Fintech. Notably, the respondents' age moderates the impact of these factors on Fintech adoption.
9. **Suryono, R. R., Budi , I., & Purwandari , B. (2020).** This study delves into the evolving landscape of financial technology (fintech), addressing its significance in the digital transformation of the financial industry. It assesses the current state of fintech research, identifies research gaps, and explores challenges and trends for future investigation. By employing systematic literature review techniques and thematic analysis, the study offers theoretical contributions to fintech research, focusing on information systems and the conceptual development of fintech technology.

RESEARCH METHODOLOGY:

1. **Research Design :** The research design for this study will be an exploratory research design. An exploratory design is chosen as it will involve data collection from participants at a single point in time, allowing for an examination of the relationships between the variables of interest of consumers in the Gujarat region.
2. **Data Collection Method :** For data collection, we have used Google Forms, an online survey tool. Participants will access and complete a structured questionnaire at their convenience through this user-friendly platform. This method will ensure data standardization, security, and efficiency, automatically organizing responses for analysis. Participants will be informed, and their privacy will be maintained throughout the process.
3. **Population:** The study's population consists of 500 random individuals with different age groups, education, and gender who are currently using any fintech services in Gujarat. These individuals collectively represent the subjects of interest for our research.
4. **Sampling technique :** The sampling technique for this study uses a convenience sampling technique where individuals are chosen based on their ease of availability and accessibility to the researcher. In this research projects participants are selected randomly who are currently using fintech services based on their accessibility and willingness to participate.
5. **Sampling Method :** For this study, a simple random sampling method has been employed, selecting the individual from Gujarat region. Random sampling is employed via Google forms which offers a convenient and efficient method for collecting data.

DATA ANALYSIS AND STATISTICS:

DEMOGRAPHIC PROFILE:

AGE: The bulk of respondents (83%) are between the ages of 21-30, indicating a sample skew toward younger demographics. Furthermore, respondents in older age groups are underrepresented, with 31-40-year-olds accounting for 9.2% and those under the age of 20 compromising 7.8% of the sample.

LOCATION: The majority of respondents come from Vadodara and Valsad, which account for more over half of the total sample (56.8%). Other places have lower representations, with some areas having only a few responders. The sample population appears to be distributed geographically in a varied manner, with Vadodara and Valsad having a substantial concentration.

GENDER: The data shows a slight majority of female respondents, accounting for 55.8% of the sample, while male respondents make up 44.2%. This indicates a relatively balanced gender representation within the sample population.

INCOME: Most of respondents (54%) have a pay of not as much as Rs 1,00,000 for every annum. There is a more modest extent of respondents with higher pay levels, with 27.4% falling inside the Rs1,00,000 - Rs5,00,000 per annum section, 14.8% inside the Rs 5,00,000 - Rs10,00,000 per annum section, and 3.8% procuring Rs10,00,000 and more per annum. This demonstrates a changed pay dissemination among the example populace, with a critical part falling into the lower level of pay.

EDUCATION: Most of the respondents (43.2%) hold advanced education, while the following biggest gathering (46.2%) are secondary school graduates. There are more modest rates of respondents with some advanced degree (7.0%), four-year certifications (0.8%), and not exactly secondary school instruction (2.8%). This recommends a different instructive foundation among the example populace, with a remarkable extent holding advanced educations.

OCCUPATION: The majority of respondents (59.2%) use Google Pay, followed by PhonePe (29.4%) and Paytm (9.4%). Bhim UPI and Zerodha have smaller representations in the sample population. This indicates a dominance of Google Pay and PhonePe among the fintech platforms used by the respondents.

TESTING HYPOTHEISI

1. PRIVACY BARRIER

H0: Concerns about DPMs privacy are not significantly correlated with demographic factor.

H1: Certain demographic groups exhibit higher levels of privacy concerns regarding DPMs.

Table : 1 Correlations

		Privacybarrier	Age:	gender	education	Income (per annum)	Occupation
Pearson Correlation	privacy barrier	1.000	.145	.096	.003	.032	.026
	Age:	.145	1.000	.007	.306	.288	.225
	Gender	.096	.007	1.000	.042	-.149	-.185
	Education	.003	.306	.042	1.000	.048	-.237
	Income (per annum)	.032	.288	-.149	.048	1.000	.421
	Occupation	.026	.225	-.185	-.237	.421	1.000
Sig. (1-tailed)	Privacybarrier	.	.001	.018	.476	.241	.284
	Age:	.001	.	.435	.000	.000	.000
	Gender	.018	.435	.	.178	.001	.000
	Education	.476	.000	.178	.	.147	.000
	Income (per annum)	.241	.000	.001	.147	.	.000
	Occupation	.284	.000	.000	.000	.000	.

Table : 2 ANOVA[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	29.490	5	5.898	3.162	.008[b]
	Residual	884.069	474	1.865		
	Total	913.559	479			

a. Dependent Variable: privacybarrier

b. Predictors: (Constant), occupation, gender, Age:, education, Income (per annum)

Table : 3 Coefficient

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	1.830	.461		3.971	.000	.925	2.736
	Age:	.528	.168	.160	3.137	.002	.197	.859
	Gender	.267	.128	.096	2.086	.038	.015	.519
	Education	-.110	.106	-.052	-1.034	.302	-.319	.099
	Income (per annum)	.009	.084	.006	.112	.911	-.156	.175
	Occupation	-.007	.055	-.007	-.127	.899	-.115	.101
a. Dependent Variable: privacybarrier								

INTERPRETATION

The correlation between privacy concerns related to DPMs and age ($r = 0.145$, $p = 0.001$), Gender ($r = 0.096$, $p = 0.018$), indicating a weak positive relationship. The correlation between privacy concerns related to DPMs and education, income, and occupation is not statistically significant , indicating no significant relationship. The ANOVA results indicate that the overall model is significant ($F = 3.162$, $p = 0.008$), suggesting demographic factor influence privacy concern related to DPMs. Therefore, we reject the null hypothesis (H0) and accept the alternative hypothesis (H1), concluding that certain demographic groups, specifically older age groups and females, exhibit higher levels of privacy concerns regarding DPMs.

2. Security Perception Hypothesis:

H0: Certain demographic groups perceive DPMs as less secure compared to others.

H1: There is no significant relationship between demographic factors and security perceptions regarding DPMs.

Table : 4 Correlations

		Privacybarrier	Age:	gender	education	Income	occupation
Pearson Correlation	Privacybarrier	1.000	.145	.096	.003	.032	.026
	Age:	.145	1.000	.007	.306	.288	.225
	Gender	.096	.007	1.000	.042	-.149	-.185
	Education	.003	.306	.042	1.000	.048	-.237
	Income	.032	.288	-.149	.048	1.000	.421
	Occupation	.026	.225	-.185	-.237	.421	1.000
Sig. (1-tailed)	Privacybarrier	.	.001	.018	.476	.241	.284
	Age:	.001	.	.435	.000	.000	.000
	Gender	.018	.435	.	.178	.001	.000
	Education	.476	.000	.178	.	.147	.000
	Income	.241	.000	.001	.147	.	.000
	Occupation	.284	.000	.000	.000	.000	.

Table : 5 Anova						
Model		Sum.Of Squares	Df	Mean Square	F	Sig.
1	Regression	10.118	5	2.024	1.457	.203[b]
	Residual	658.414	474	1.389		
	Total	668.531	479			
a. Dependent Variable: securitybarrier						
b. Predictors: (Constant), occupation, gender, Age:, education, Income (per annum)						

Table: 6 Cofficient

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2.240	.398		5.631	.000	1.458	3.021
	Age:	.189	.145	.067	1.300	.194	-.097	.474
	Gender	.161	.110	.068	1.460	.145	-.056	.378
	Education	.058	.092	.032	.635	.526	-.122	.238
	Income.	-.100	.073	-.071	-1.372	.171	-.242	.043
	Occupation	.002	.047	.002	.043	.966	-.091	.095
a. Dependent Variable: securitybarrier								

INTERPRETATION

The correlation between security perceptions regarding DPMs and age, gender, education, income, occupation, is not statistically significant indicating no significant relationship. Therefore, the ANOVA results indicate that the overall model is not significant ($F = 1.457$, $p = 0.203$), suggesting that the predictors (age, gender, education, income, occupation) do not significantly predict security perceptions regarding DPMs. Therefore, we fail to reject the null hypothesis (H0) and conclude that there is no significant relationship between demographic factors and security perceptions regarding DPMs.

3. Access and Technical Barrier Hypothesis:

H0: There is no significant relationship between demographic factors and perceived access barriers or technical issues with DPMs.

H1: Older age groups and individuals with lower education levels are more likely to encounter access barriers and technical problems with DPMs.

Table: 7 Correlations				
		Access barrier	Age:	Education
Pearson Correlation	Access barrier	1.000	.094	.108
	Age:	.094	1.000	.294
	Education	.108	.294	1.000
Sig. (1-tailed)	Accessbarrier	.	.018	.008
	Age:	.018	.	.000
	Education	.008	.000	.

Table: 8 ANOVA[a]						
Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	13.474	2	6.737	3.976	.019[b]
	Residual	835.400	493	1.695		
	Total	848.874	495			
a. Dependent Variable: accessbarrier						
b. Predictors: (Constant), education, Age:						

Table: 9 Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2.161	.369		5.857	.000	1.436	2.886
	Age:	.215	.148	.068	1.455	.146	-.075	.505
	Education	.173	.092	.088	1.881	.061	-.008	.354
a. Dependent Variable: accessbarrier								

<u>INTERPRETATION</u>

The correlation between perceived access barriers or technical issues with DPMs and age,($r = 0.094$, $p = 0.018$) and education ($r = 0.0108$, $p = 0.008$), which is statistically significant indicating a weak positive relationship.The ANOVA results indicate that the overall model is significant ($F = 3.976$, $p = 0.019$), suggesting that older age ad lower education group has a significant effect on perceived access barriers or technical issues with DPMs. Therefore, we reject the null hypothesis (H0) and accept the alternative hypothesis (H1).

4. Impersonalization Concerns Hypothesis:

H0: There is no significant relationship between demographic factors and concerns related to impersonalization in DPM transactions.

H1: Younger age groups and individuals with higher education levels are less likely to find impersonalization as a barrier to using DPMs.

Table: 10 Correlations				
		Impersonalization barrier	Age:	Education
Pearson Correlation	Impersonalizationbarrier	1.000	.068	.145
	Age:	.068	1.000	.294
	Education	.145	.294	1.000
Sig. (1-tailed)	Impersonalizationbarrier	.	.065	.001
	Age:	.065	.	.000
	Education	.001	.000	.

Table: 11 ANOVA[a]						
Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	16.155	2	8.078	5.508	.004[b]
	Residual	723.019	493	1.467		
	Total	739.174	495			

a. Dependent Variable: impersonalizationbarrier
b. Predictors: (Constant), education, Age:

Table: 12 Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2.018	.343		5.879	.000	1.344	2.692
	Age:	.081	.137	.028	.592	.554	-.189	.352
	Education	.252	.086	.137	2.948	.003	.084	.421
a. Dependent Variable: impersonalizationbarrier								

INTERPRETATION

The correlation between concerns related to impersonalization in DPM transactions and age is ($r = 0.068$, $p = 0.065$), which is not statistically significant and education ($r = 0.145$, $p = 0.001$) which is statistically significant. The ANOVA results indicate that the overall model is significant ($F = 5.508$, $p = 0.004$), suggesting that individuals with higher education levels are less likely to find impersonalization as a barrier. Therefore, we reject the null hypothesis (H0) and accept the alternative hypothesis (H1) concluding there is no significant evidence to suggest a relationship between age and concerns related to impersonalization in DPM transactions.

5. Trust and Credibility Hypothesis:

H0: There is no significant relationship between demographic factors and levels of trust and credibility in DPMs.

H1: Higher income groups and individuals with higher education levels exhibit higher levels of trust and credibility in DPMs.

Table: 13 Correlations				
		TrustandCredibility	Income (per annum)	Education
Pearson Correlation	TrustandCredibility	1.000	.069	.117
	Income (per annum)	.069	1.000	.065
	Education	.117	.065	1.000
Sig. (1-tailed)	TrustandCredibility	.	.061	.004
	Income (per annum)	.061	.	.074
	Education	.004	.074	.

Table: 14 Coefficients								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2.201	.297		7.420	.000	1.618	2.783
	Education	.206	.081	.113	2.533	.012	.046	.366
	Income	.089	.064	.062	1.387	.166	-.037	.216

Table: 15 ANOVA[a]						
Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	12.733	2	6.367	4.416	.013[b]
	Residual	710.802	493	1.442		
	Total	723.536	495			
a. Dependent Variable: TrustandCredibility						
b. Predictors: (Constant), Income (per annum), education						

INTERPRETATION

The correlation between levels of trust and credibility in DPMs and education (r = 0.117, p = 0.004) is statistically significant and income is (r = 0.069, p = 0.061) is not statistically significant. The ANOVA results indicate that the overall model is significant (F = 4.416, p = 0.013). Therefore, we reject the null hypothesis (H0) and accept the alternative hypothesis (H1), concluding that individuals with higher education levels exhibit higher levels of trust and credibility in DPMs. However, there is no significant evidence to suggest a relationship between income (per annum) and levels of trust and credibility in DPMs.

6. Ease-of-Use and Usefulness Hypothesis:

H0: There is no significant relationship between demographic factors and perceptions of ease-of-use and usefulness of DPMs.

H1: Younger age groups and individuals with higher education levels find DPMs more convenient and useful compared to others.

Table:16 Correlations				
		easetouseandusefulness	Education	Age:
Pearson Correlation	Easetouseandusefulness	1.000	.124	.080
	Education	.124	1.000	.294
	Age:	.080	.294	1.000
Sig. (1-tailed)	Easetouseandusefulness	.	.003	.038
	Education	.003	.	.000
	Age:	.038	.000	.

Table: 17 ANOVA[a]						
Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	17.146	2	8.573	4.398	.013[b]
	Residual	960.980	493	1.949		
	Total	978.126	495			
a. Dependent Variable: easetouseandusefulness						
b. Predictors: (Constant), Age:, education						

Table: 18 Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2.038	.396		5.151	.000	1.261	2.816

	Education	.233	.099	.110	2.364	.018	.039	.427
	Age:	.161	.159	.047	1.017	.310	-.150	.473
a. Dependent Variable: easetouseandusefulness								

INTERPRETATION

The correlation between perceptions of ease-of-use and usefulness of DPMs and education is (r = 0.124, p = 0.003),which is statistically significant and age is (r = 0.080, p = 0.038), which is statistically significant. The ANOVA results indicate that the overall model is significant (F = 4.398, p = 0.013), suggesting that at least one of the predictors (education, age) has a significant effect on perceptions of ease-of-use and usefulness of DPMs. Therefore, we reject the null hypothesis (H0) and accept the alternative hypothesis (H1), concluding that younger age groups and individuals with higher education levels find DPMs more convenient and useful compared to others.

7. Social Influence Hypothesis:

H0: There is no significant relationship between demographic factors and social influence in adopting DPMs.

H1: Younger age groups and individuals with higher income levels are more influenced by peers and social norms in adopting DPMs.

Table: 19 Correlations

		socialinflueceba rrierbreake	Age:	Income (per annum)
Pearson Correlation	Socialinfluecebarrierbreake	1.000	.063	.056
	Age:	.063	1.000	.272
	Income (per annum)	.056	.272	1.000
Sig. (1-taied)	Socialinfluecebarrierbreake	.	.080	.105
	Age:	.080	.	.000
	Income (per annum)	.105	.000	.

Table: 20 Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2.453	.291		8.424	.000	1.881	3.025
	Age:	.162	.146	.052	1.109	.268	-.125	.449
	Income (per annum)	.063	.070	.042	.906	.366	-.074	.201

Table: 21 ANOVA[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	4.697	2	2.349	1.402	.247[b]
	Residual	832.555	497	1.675		
	Total	837.252	499			

a. Dependent Variable: socialinfluecebarrierbreake
b. Predictors: (Constant), Income (per annum), Age:

INTERPRETATION

The correlation between social influence in adopting DPMs and age is 0.063, and income (per annum) is 0.056. However, neither correlation is statistically significant at the 0.05 level ($p > 0.05$). The ANOVA results also indicate that the overall model is not significant ($F = 1.402$, $p = 0.247$), suggesting that neither age nor income significantly predict susceptibility to social influence in adopting DPMs. Therefore, we fail to reject the null hypothesis (H0), concluding that there is no significant relationship between demographic factors and social influence in adopting DPMs.

8. Intention to Fully Adopt DPMs Hypothesis:

H0: There is no significant relationship between demographic factors and intention to fully adopt DPMs in the future.

H1: Younger age groups and individuals with higher income levels are more likely to express intentions to fully adopt DPMs in the future.

Table: 22 Correlations

		intentiontofullyadoptdpms	Age:	Income (per annum)
Pearson Correlation	Intentiontofullyadoptdpms	1.000	.083	.074
	Age:	.083	1.000	.272
	Income (per annum)	.074	.272	1.000
Sig. (1-tailed)	Intentiontofullyadoptdpms	.	.032	.049
	Age:	.032	.	.000
	Income (per annum)	.049	.000	.

Table: 23 ANOVA[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	11.329	2	5.664	2.443	.088[b]
	Residual	1152.303	497	2.319		
	Total	1163.632	499			
a. Dependent Variable: intentiontofullyadoptdpms						
b. Predictors: (Constant), Income (per annum), Age:						

Table - 24 Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2.474	.343		7.221	.000	1.801	3.147
	Age:	.250	.172	.067	1.455	.146	-.088	.587
	Income (per annum)	.099	.082	.056	1.206	.228	-.062	.261
a. Dependent Variable: intentiontofullyadoptdpms								

INTERPRETATION

According to ANOVA results (p = 0.088), demographic characteristic and intention to fully adopt DPMs indicate that there is no significant relationship. Age and income do not has a statistically significant effect on intention to fully adopt DPMs, according to coefficient (both p-values > 0.05). therefore, we reject alternative hypothesis and accepts null hypothesis concluding that there is no significant evidence to support the hypothesis that younger age groups and individuals with higher income levels are more likely to express intentions to fully adopt DPMs in the future.

FINDINGS

1. Protection concerns connected with Advanced Installment Strategies (DPMs) are affected by segment factors like age and orientation, with more seasoned age gatherings and females displaying more elevated levels of security concerns.
2. Security insights in regards to DPMs are not essentially affected by segment factors like age, orientation, schooling, pay, or occupation.
3. Access obstructions and specialized issues with DPMs are bound to be experienced by more established age gatherings and people with lower schooling levels.
4. Concerns connected with impersonalization in DPM exchanges are essentially impacted by schooling, with people with advanced education levels being less inclined to track down impersonalization as a boundary to utilizing DPMs.
5. Levels of trust and believability in DPMs are essentially impacted by schooling, with people with advanced education levels displaying more elevated levels of trust and validity.
6. Impression of convenience and value of DPMs are fundamentally impacted by schooling and age, with more youthful age gatherings and people with advanced education levels finding DPMs more helpful and valuable.
7. Powerlessness to social impact in embracing DPMs isn't altogether affected by segment factors like age and pay.
8. There is no critical connection between segment elements and expectation to embrace DPMs in the future completely.

CONCLUSION

In conclusion, there are a number of factors that impact the adoption of digital payment methods (DPMs), such as trust issues, impersonalization, security risks, privacy concerns, and access restrictions. Age and education are two demographic characteristics that are linked to these barriers, though the relationship is not always strong in all DPM adoption contexts. However, these difficulties can be lessened and increased adoption can be encouraged by barrier breakers like perceived usefulness, ease of use, social influence, and credibility. In order to encourage a broad acceptance of DPMs, stakeholders need to solve issues related to security and privacy, enhance accessibility, humanize digital interactions, and foster trust through open and honest practices. Legislators and industry participants can promote financial inclusion and enable people to benefit from digital payments by giving careful consideration to these aspects.

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