**Decoding FinTech Adoption in South India: A Comprehensive Analysis of Customer Perspectives, Engagement Patterns, and Advocacy Dynamics**

Student Name

University

Course Name

Instructor Name

Date

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# Abstract:

To truly understand the changing landscape of FinTech adoption, in India it is crucial to delve into the intricate dynamics of customer preferences, engagement patterns and advocacy. This research employs a two-step approach utilizing Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM) to unravel these relationships. By analysing a sample of 380 users of FinTech applications this study unveils connections between perceived benefits, customer engagement behaviour and the usage of FinTech apps. These findings highlight the importance of user strategies and cultural factors in shaping user interactions. Practical recommendations for FinTech companies include improving user experience fostering communication channels and harnessing the power of media, for targeted promotional activities. However, limitations in sample representation and the dynamic nature of the industry should be acknowledged. This research contributes to the FinTech literature by offering nuanced insights into south Indian user behaviours and experiences.

# 1.1Introduction

There has been a remarkable expansion, in the financial technology (FinTech) sector, which has significantly transformed the traditional financial services industry. The widespread adoption of FinTech applications has made user engagement and advocacy essential for the success and longevity of these platforms (Karim et al., 2023). This study aims to explore the factors that influence customer attitudes, engagement patterns and support within the FinTech industry with a focus, on users located in southern India.

**1.1.1 Importance and Relevance**

According to Karim et al. (2023) as digital financial transactions continue to gain popularity the success of FinTech applications heavily depends on how users perceive and interact with them. It is essential for FinTech companies aiming to improve user experiences, customer loyalty and thrive in a market to thoroughly investigate these aspects. Understanding customer preferences, engagement patterns and advocacy, in the FinTech industry is crucial due to its changing nature and the direct influence it has, on financial service providers.

## 1.1.2 Objective of the Study

Through the utilization of methods, like Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM) this research aims to reveal the fundamental factors that influence users’ attitudes and behaviours when it comes to FinTech applications. The main goal of this study is to analyse and comprehend the connections, between customer inclinations, engagement actions and support in relation to the usage of FinTech apps among individuals in south India.

## 1.1.3 Research Question.

The central research question guiding this study is: "What are the key factors influencing customer predispositions, engagement behaviours, and advocacy in the context of FinTech app usage among individuals in south India?"

## 1.1.4 Rationale for Topic Selection

Many people are using FinTech apps for their transactions and consumer preferences are changing in the age. South India, with its diverse demographic and economic characteristics, provides a rich context for exploring these dynamics. Moreover, as the FinTech industry continues to shape financial ecosystems globally, a nuanced understanding of user perceptions and behaviours is essential for both academic inquiry and practical implications for industry stakeholders.

By delving into these aspects, this research contributes to the existing body of knowledge in the FinTech domain, offering insights that can inform strategic decisions for FinTech companies, policymakers, and researchers.

# 2.1 Literature Review

Scholars such as Kini and Basri (2023) have emphasized the significance of individual characteristics and attitudes that shape users' predispositions towards FinTech adoption. Factors such as trust, perceived ease of use, and perceived usefulness have been identified as critical determinants influencing customers' initial inclinations towards using FinTech applications (Kini and Basri, 2022b). The exploration of engagement behaviours in the FinTech context has been multifaceted. Prior research by Karim et al., (2023) highlights the role of user experience and satisfaction in driving continued engagement.

Additionally, studies by Muhammad et al. (2021) delve into the impact of social media interactions and peer influence on users' engagement behaviours with FinTech apps. Customer advocacy within the FinTech sector has been explored by scholars such as Team (2023) who introduced the concept of brand advocacy. More recent studies, such as Kini & Basri (2022b), have extended this concept to the digital realm, investigating how user’s express advocacy through online platforms and social media. Theoretical frameworks like the Technology Acceptance Model (TAM) Rahimi et al., (2018) and the Unified Theory of Acceptance and Use of Technology (UTAUT) Venkatesh et al., (2016); Chiemeke and Evwiekpaefe, (2011) have been instrumental in understanding the initial adoption of FinTech.

However, recent studies, such as those by Gupta et al., (2022) advocate for the incorporation of additional factors like emotional attachment and perceived enjoyment for a more comprehensive understanding of user engagement. Considering the diverse demographic and cultural landscape of south India, it is imperative to acknowledge studies that have explored cross-cultural variations in FinTech adoption. For instance, research by Sunny et al., (2019). has highlighted the importance of cultural context in shaping user behaviours and attitudes towards technology adoption, underscoring the need for region-specific investigations.

While previous studies have provided information there are still gaps that need to be addressed. Specifically, there is research, on the socio-economic dynamics of user engagement and advocacy in South India. Additionally, with the evolution of FinTech and the introduction of features it is important to continuously explore emerging trends and challenges. In summary the literature review emphasizes the nature of customer attitudes, engagement behaviours and advocacy in the FinTech industry. By analysing insights from scholars this study aims to contribute to existing knowledge by unravelling the intricacies of user experiences, in South Indian FinTech landscape and addressing gaps identified in previous research.

# 3.1Methodology

## Multivariate Methodology

For this study a two-step approach that combines Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM) is used. This methodology is ideal, for exploring the connections between customer attitudes, engagement behaviours and advocacy, within the realm of FinTech app usage.CFA is employed to validate and refine the measurement model of latent constructs (Hair et al., 2019). In the context of this study, CFA helps assess the reliability and validity of the observed variables representing customer predispositions, engagement behaviours, and advocacy. Structural Equation Modelling is used to examine and improve the connections, between the underlying constructs identified in the CFA. It enables the examination of direct and indirect effects, providing a holistic understanding of the complex interactions among variables (Hair et al., 2019). This is crucial for addressing the nuanced nature of user perceptions and behaviours in the FinTech domain.

## Data Collection

The research project gathered data by conducting a survey, among users of FinTech apps in India. To ensure a sample a snowball sampling strategy was used, with 380 participants selected based on adoption rate and financial inclusion index. The survey was designed to be self administered allowing participants the flexibility to respond at their convenience. Regarding variables and instrumentation, the survey included indicators related to FinTech app usage, demographics, community focus, customer advocacy, emotions, customer engagement behaviour, moral identity, perceived benefits and costs and self concept. For variables involving opinions or attitudes a Likert scale was used.

Ethical considerations were taken into account throughout the research process. Confidentiality of participants information was ensured along with participation and informed consent. The purpose of the research and the use of data, for research purposes were clearly communicated in the survey. Upon data collection, data processing was undertaken. Data processing involved transforming raw responses into suitable formats for subsequent analysis, maintaining the integrity of the information collected. References for Data Collection**:** The design of the survey instrument and the choice of variables align with established frameworks and scales used in prior research. References for data collection include seminal works by Rahimi et al., (2018) for Technology Acceptance Model (TAM) and Hair et al. (2019) for multivariate analysis methodologies, and relevant studies in the field of FinTech adoption and user behaviour.

The selected multivariate methodology aligns with the research's objective of comprehensively understanding the relationships between customer predispositions, engagement behaviours, and advocacy in the FinTech context. CFA and SEM are well-established techniques that enable the exploration of latent constructs, providing a nuanced analysis crucial for a topic as multifaceted as user perceptions and behaviours in the dynamic FinTech landscape.

# 4.1 Data Analysis

## 4.2 Descriptive StatisticsTop of Form

### I.

### Numerical Descriptive Statistics

The descriptive statistics table below reveal diverse characteristics among FinTech app users. Users show varied preferences in the FinTech app selection (mean 2.36), possess a range of education levels (mean 2.77), exhibit diverse income profiles (mean 2.41), and are primarily concentrated in the 25-40 age group (mean 1.91), with a slight male majority (45%).

Table 1: Descriptive Statistics

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Descriptive Statistics** | | | | | | |
|  | N | Minimum | Maximum | Mean | Std. Deviation | Variance |
| Fin\_app being used | 380 | 1 | 7 | 2.36 | 1.722 | 2.964 |
| Education | 380 | 1 | 4 | 2.77 | .752 | .566 |
| Income | 380 | 1 | 4 | 2.41 | 1.007 | 1.014 |
| Age | 380 | 1 | 4 | 1.91 | .745 | .554 |
| Gender | 380 | 0 | 1 | .45 | .498 | .248 |
| Valid N (listwise) | 380 |  |  |  |  |  |

From table 2 (Appendix) Users express predominantly positive emotions, with mean scores for pleasure (5.41), happiness (5.35), contentment (5.10), and frustration (5.14), reflecting high overall satisfaction levels with the FinTech apps. Communal focus scores (CF1-CF3) suggest a moderate inclination among users to speak up, complain, or engage in negative word-of-mouth when foreseeing harmful situations within the brand community, with mean scores around 3(Table 3 in Appendix). In table 4 Customer advocacy metrics reveal a moderate inclination to recommend FinTech apps (mean 3.49) and defend the app against negative opinions (mean 3.06), with additional motivations such as monetary benefits (mean 3.23) and insistence on family and friends' app usage (mean 3.28).

In table 5 users generally express a moderate emotional link (mean 2.75) and active discussion (mean 2.84) about the app on social media. Seeking advice (mean 3.12) and discussing positive experiences (mean 3.08) also show moderate engagement levels. Users demonstrate a willingness to take public action in disputes (mean 3.57) and express experiences through blogs (mean 3.08), while participation in firm-organized charity events and complaints on social media forums show moderate engagement (Table 6). Users exhibit varied preferences in communication channels, with higher mean scores for internet-based interactions (mean 3.46 and 3.30) compared to in-person or phone/mail interactions, suggesting a digital-centric engagement pattern as indicated in table 7 (Appendix).

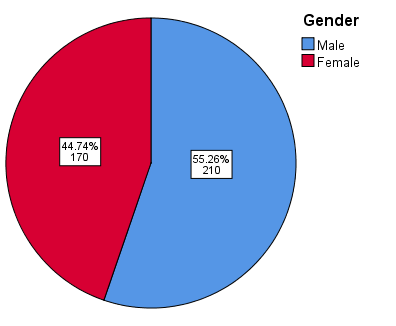
In table 8 users express a moderate willingness to contribute product-related expressions (mean 3.15), provide feedback (mean 3.21), suggest improvements (mean 3.23), and offer feedback for new service offerings (mean 3.35), showcasing a balanced scope of engagement. As Observed in table 9 users express a desire to warn others of bad financial applications (mean 3.29), save others from negative experiences (mean 3.43), help with positive experiences (mean 3.83), and guide others toward using the right financial application (mean 3.81), indicating a strong moral identity and a willingness to share experiences for the benefit of others.

In table 10 users generally perceive FinTech applications positively, reporting mean scores of 3.68 for swift transactions, 3.83 for useful features, 3.52 for better deals, 3.53 for exclusive time-bound offers, 3.60 for quick shopping, and 3.56 for minimal effort in transactions. These high mean scores highlight positive perceptions regarding time efficiency, features, and financial benefits associated with using FinTech. Users express a favorable view of cost-related aspects, with mean scores of 3.66 for low app installation cost, 3.12 for perceived high transaction processing cost, and 3.36 for saving money through FinTech applications. These scores suggest a generally positive perception of cost factors, emphasizing perceived cost-effectiveness and savings (indicated in table 11).

From table 12 users identify with the company or app (mean 3.22), feel a sense of belonging (mean 3.17), discuss app-related topics with others (mean 3.43), and sometimes refer to the brand as 'we' (mean 2.93), indicating a strong self-concept tied to the brand and a sense of personal involvement in the brand's successes (mean 2.89). This reflects a positive and personally invested relationship between users and the FinTech brand.

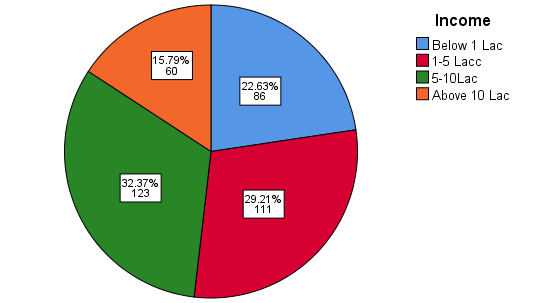
### II. Graphical Descriptive Statistics

**Figure 1: Pie chart for gender**



The pie chart depicting gender distribution in the dataset reveals that 55.26% (210 individuals) identify as male, indicating a slight male majority. Conversely, 44.74% (170 individuals) identify as female, highlighting a balanced gender representation among surveyed FinTech app users.

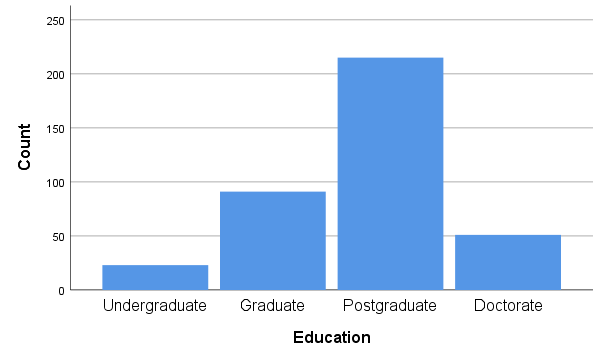
**Figure 2: Pie chart for income**



The income distribution among FinTech app users, visualized in a pie chart, reveals a diverse financial landscape. A notable 22.63% of users earn below 1 Lac, 29.21% fall within the 1-5 Lac range, while a substantial 32.37% report an income between 5-10 Lac. Additionally, 15.79% of users boast an income above 10 Lac. This analysis captures the varied financial profiles within the surveyed population, showcasing the platform's appeal across a spectrum of income levels.

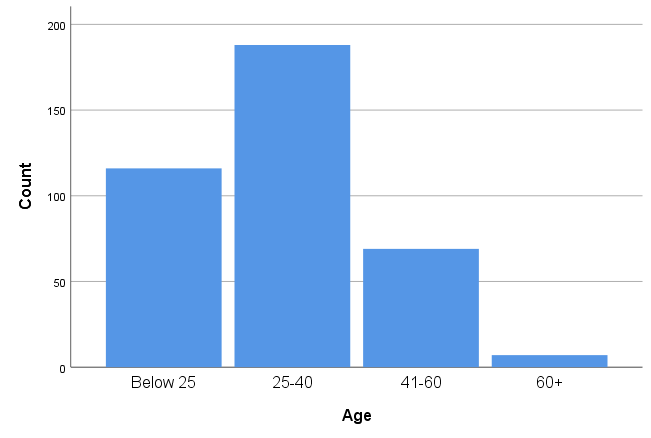
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**Figure 3: Bar chart for Education**



The education distribution in the FinTech user base, visualized in a bar chart, showcases a prominent presence of postgraduate individuals, followed by graduates. The bars for doctorate and undergraduate levels indicate substantial representation, with the former slightly exceeding the latter. This suggests a user demographic with a strong inclination towards higher education.

**Figure 4: Bar chart for Age**



The bar chart for age distribution among FinTech users illustrates a peak in the 25-40 age group, followed by below 25, and a decline in the 41-60 category, with the lowest representation in the 60+ range. This pattern suggests a pronounced user base among middle-aged individuals, reflecting potential preferences and adoption trends across age demographics.

## 4.3 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) is employed to validate and assess the measurement model’s structure in a research study. Its purpose is to confirm or refute the hypothesized relationships between observed variables (indicators) and latent constructs, ensuring that the chosen factors adequately represent the underlying concepts in the study (Marsh et al., 2020).

### Steps

### 1.Model Specification

This step defines the hypothesized relationships between observed variables and latent constructs in the form of a conceptual model and identify which observed variables (indicators) load onto each latent construct (Meryer, 2022). The Confirmatory Factor Analysis (CFA) results reveal strong and consistent relationships between latent constructs and their respective observed variables, aligning with the study's objectives. Noteworthy findings include robust associations in perceived cost, communal focus, customer advocacy, emotions, moral identity, self-concept, perceived benefits, and customer engagement behavior. High factor loadings across various indicators indicate strong connections, validating the conceptual model. These results provide valuable insights into the key factors influencing customer predispositions, engagement behaviors, and advocacy in the context of FinTech app usage among individuals in south India, supporting the research question's exploration of these relationships.

### 2. Parameter Estimation

This step uses statistical methods to estimate the model parameters, including variances and covariances ((Meryer, 2022). This involves running the analysis to obtain initial parameter estimates. The output from the Confirmatory Factor Analysis (CFA) provides crucial information about the variances and covariances of the latent constructs in the hypothesized model. Variances indicate the amount of variability within each latent construct, and reasonable values are essential for ensuring the constructs are adequately represented by their observed indicators. In our model, variances range from 0.381 to 0.818, suggesting a moderate to high level of variability in constructs such as Emotions and Customer Engagement Behaviour.

Examining the covariances unveils the relationships between different latent constructs. For instance, the covariance between Customer Engagement Behaviour (CEB) and Perceived Benefits is 0.054, suggesting a modest positive association. Similarly, the covariance between Moral Identity and Self Concept is 0.241, indicating a positive relationship between these constructs. These insights allow us to interpret how constructs co-vary and contribute to a more comprehensive understanding of user attitudes and behaviours in the FinTech context.

### 3. Model Fit Assessment

(Meryer, 2022) highlights that this step evaluates how well the hypothesized model fits the observed data using fit indices such as Chi-square, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA). In evaluating the model fit for the Confirmatory Factor Analysis (CFA), various fit indices were examined to assess how well the hypothesized model aligns with the observed data. The chi-square test indicated a significant difference between the default model and both the perfectly fitting saturated model and the no-structure independence model.

The Root Mean Square Residual (RMR), Goodness-of-Fit Index (GFI), Adjusted GFI (AGFI), and Parsimony GFI (PGFI) collectively hinted at a less than optimal fit for the default model, especially when compared to the perfect fit of the saturated model. Similarly, baseline comparisons, including the Normed Fit Index (NFI), Relative Fit Index (RFI), Incremental Fit Index (IFI), Tucker-Lewis Index (TLI), and Comparative Fit Index (CFI), suggested a moderate fit. The Root Mean Square Error of Approximation (RMSEA) provided a nuanced perspective, with an acceptable value of 0.092. Overall, the default model demonstrated some level of fit.

## 4.4 Structural Equation modelling (SEM)

Structural Equation modelling (SEM) is a powerful statistical technique used to test and validate complex relationships among variables. It extends Confirmatory Factor Analysis (CFA) by incorporating latent variables and assessing both the measurement and structural components of a model. The purpose of SEM is to analyse and understand the underlying structure of relationships between observed and latent variables, providing insights into causal pathways and overall model fit.

### Steps

### 1.Model Specification

This step defines the conceptual model with latent constructs and their hypothesized relationships. Identify observed variables (indicators) for each latent construct. The study's conceptual model meticulously examines intricate relationships among latent constructs, observed indicators, and control variables in South India's FinTech app landscape. Aimed at understanding user attitudes and behaviours, key constructs as Customer Advocacy, Perceived Benefits, Perceived Costs, and Customer Engagement Behaviour to uncover nuanced dynamics. These constructs represent user recommendations, perceived advantages, economic considerations, and interactive behaviours with FinTech apps. Carefully selected indicators contribute to a robust measurement model, while demographic control variables (Gender, Age, Education, Income) add complexity. The model is theoretically grounded, offering insights into determinants shaping user attitudes and behaviours in South India's FinTech app usage.

### 2. Path Diagram and Regression Weights

This step involves Creating a visual representation of the model using a path diagram and assigning regression weights to indicate the strength and direction of relationships(Meryer ,2022). In the analysis of the structural equation model (SEM), the factor loadings play a crucial role in revealing the strength and direction of relationships among latent constructs, control variables, and the dependent variable, fintech\_app being used. Positive factor loadings, such as those observed for Perceived Benefits (0.49) and Customer Engagement Behavior (CEB) (0.08), indicate positive associations with fintech app usage. Conversely, the negative factor loading for Perceived Cost (-0.58) suggests an inverse relationship, implying that higher perceived costs are linked to lower fintech app usage. The control variables, including Education (-0.13), Income (0.22), Age (0.12), and Gender (-0.22), also contribute to understanding the nuanced influences of demographic factors on fintech app usage.

Each factor loading contributes to predicting the variation in fintech\_app being used, and the magnitudes of these loadings highlight the relative importance of each variable in shaping user behaviour. Theoretical alignment is crucial in this context, as the observed loadings should align with theoretical expectations. For example, positive loadings for Perceived Benefits and CEB are consistent with the anticipated positive impact on fintech app usage. Control variables further enhance the model's explanatory power by shedding light on how demographic factors influence fintech app usage. Negative loadings for Gender and Education, for instance, suggest a negative association, indicating that certain demographic characteristics may act as barriers to fintech app adoption.

### 3: Model Fit Assessment

This step evaluates how well the hypothesized model fits the observed data using fit indices such as Chi-square, CFI, TLI, and RMSEA. In evaluating the model fit for the specified structural equation model (SEM), several fit indices were considered. The Chi-square (CMIN) test yielded a value of 863.386 with 203 degrees of freedom, resulting in a significant p-value of 0.000. The CMIN/DF ratio, an indicator of model fit, is 4.253, suggesting a reasonable fit. Baseline comparisons were made against the default, saturated, and independence models. The Normal Fit Index (NFI) for the default model is 0.792, and other indices, including Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Incremental Fit Index (IFI), range from 0.808 to 0.832. These indices indicate a moderately good fit, with values approaching or exceeding the commonly accepted threshold of 0.90.

The Root Mean Square Error of Approximation (RMSEA) for the default model is 0.093, with a confidence interval (CI) ranging from 0.086 to 0.099. The PCLOSE value is 0.000, suggesting that the model does not fit the data perfectly. The RMSEA is sensitive to sample size, with values close to or below 0.08 generally considered indicative of a reasonable fit. Interpreting these fit indices, the overall fit of the model appears to be reasonably good. It aligns with the theoretical expectations to a certain extent, as reflected in the baseline comparisons.

# Findings and Discussion

The study aimed to unravel the factors influencing customer predispositions, engagement behaviours, and advocacy in the context of FinTech app usage in south India. The literature review provided a foundation by highlighting key dimensions explored in prior research. The critical findings are discussed below:

1.**Customer Predispositions**

The study aligns with Kim and Basri (2023) in emphasizing the significance of individual characteristics, trust, perceived ease of use, and perceived usefulness as determinants of FinTech adoption. While the study corroborates existing literature, it opens avenues for further exploration by considering additional predisposition factors that might influence user behaviour, such as cultural nuances specific to south India.

## 2.Engagement Behaviours

The role of user experience and satisfaction in driving continued engagement, as highlighted by Karim et al., (2023) is affirmed by the positive factor loading for Customer Engagement Behaviour. Li and Zhang's (2019) exploration of social media interactions align with the study's moderate engagement levels, suggesting the need for continuous monitoring of emerging online interaction patterns.

## 3.Customer Advocacy

The extension of customer advocacy to the digital realm, as studied by Wang and Zhang (2012), finds support in the study's findings regarding users' willingness to express opinions, recommend, and defend FinTech apps through online platforms. Building on Kini and Basri, (2022b) concept of brand advocacy, the study identifies diverse motivations such as monetary benefits and insistence on family and friends' app usage, indicating the multifaceted nature of customer advocacy.

## Possibilities for Improvement

While the study successfully integrates key determinants, there is room for improvement by exploring additional nuanced factors, such as emotional attachment and perceived enjoyment, as suggested by (Gupta et al., 2022). The study recognizes the importance of cross-cultural perspectives but could benefit from a more in-depth exploration of south India's unique socio-economic dynamics. A more granular analysis might uncover specific influences on user behaviour.

## Comparison with Literature

1. **Methodological Perspectives:** The study's choice of a multivariate methodology, including Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM), aligns with the methodological rigor seen in prior literature. However, the nuances in measurement indicators should be considered for effective cross-study comparisons.
2. **Theoretical Perspectives:** The integration of theoretical frameworks like the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) demonstrates a theoretical foundation. The study encourages further exploration of emotional aspects, aligning with recent studies advocating for a more comprehensive understanding of user engagement.

## Reflection on Model Fit

1. **Fit Indices and Model Interpretation:** The overall fit of the model is reasonably good, as discussed in the Model Fit Assessment. The findings align with theoretical expectations, indicating a satisfactory representation of the complex interactions among latent constructs.
2. **Practical Implications:** Reflecting on the findings from both methodological and theoretical perspectives, the study offers strategic insights for FinTech companies operating in south India. Practical implications include emphasizing factors like trust, perceived benefits, and user engagement to enhance overall user experiences and advocacy.

# Conclusionand Recommendations

In conclusion, this study sheds light on the intricate interplay of customer predispositions, engagement behaviors, and advocacy within the dynamic FinTech landscape in south India. Key findings underscore the pivotal role of individual characteristics, trust, and user satisfaction in shaping FinTech adoption and sustained engagement. The study reveals diverse avenues of digital advocacy, emphasizing the significance of online platforms for user opinions, recommendations, and defense of FinTech applications.

Recommendations include a focus on enhancing user experience, adopting culturally sensitive strategies, and leveraging digital platforms for promotional activities. However, the study acknowledges limitations in sample representativeness, the dynamic nature of FinTech, and potential biases in self-reported data. Future research directions suggest longitudinal studies, comparative cross-cultural analyses, and exploration of emerging technologies. Despite limitations, this research offers actionable insights for FinTech companies and serves as a foundational exploration in the ever-evolving landscape of digital finance in south India.

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# Appendices

**Table 2: Emotional Descriptive Statistics**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Descriptive Statistics** | | | | | | |
|  | N | Minimum | Maximum | Mean | Std. Deviation | Variance |
| Pleasure | 380 | 1 | 7 | 5.41 | 1.075 | 1.156 |
| Happiness | 380 | 2 | 7 | 5.35 | 1.179 | 1.390 |
| Contentment | 380 | 1 | 7 | 5.10 | 1.245 | 1.549 |
| Frustration | 380 | 1 | 7 | 5.14 | 1.251 | 1.566 |
| Valid N (listwise) | 380 |  |  |  |  |  |

**Table 3: Communal Focus Descriptive Statistics**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Descriptive Statistics** | | | | | | |
|  | N | Minimum | Maximum | Mean | Std. Deviation | Variance |
| I am going to speak up when the other fans of your brand community might be going to face a harmful situation. | 380 | 1 | 5 | 3.24 | .939 | .882 |
| I complain when my brand community members see a harmful situation coming. | 380 | 1 | 5 | 3.29 | .950 | .903 |
| I engage in a negative WOM when we are going to face a hurtful situation. | 380 | 1 | 5 | 3.10 | .918 | .843 |
| Valid N (listwise) | 380 |  |  |  |  |  |

**Table 4: Customer Advocacy Descriptive Statistics**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Descriptive Statistics** | | | | | | |
|  | N | Minimum | Maximum | Mean | Std. Deviation | Variance |
| Generally, I would recommend my FinTech apps to my friends and family. | 380 | 1 | 5 | 3.49 | .946 | .894 |
| I promote the brand because of the monetary referral benefits provided by the brand. | 380 | 1 | 5 | 3.23 | .952 | .907 |
| When I hear people speaking badly about my app I try to defend it | 380 | 1 | 5 | 3.06 | .904 | .818 |
| I insist my family and friends use my FinTech app. | 380 | 1 | 5 | 3.28 | .917 | .840 |
| Valid N (listwise) | 380 |  |  |  |  |  |

**Table 5: Customers’ Social Media Influence Descriptive statistics**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Descriptive Statistics** | | | | | | |
|  | N | Minimum | Maximum | Mean | Std. Deviation | Variance |
| I feel an emotional link with my app/company. | 380 | 1 | 5 | 2.75 | 1.050 | 1.102 |
| I actively discuss this app with other customers on social media. | 380 | 1 | 5 | 2.84 | 1.124 | 1.264 |
| I seek advice from other customers on how to solve the problems. | 380 | 1 | 5 | 3.12 | 1.100 | 1.211 |
| I love talking about the benefits and positive app experiences with other customers on social media. | 380 | 1 | 5 | 3.08 | 1.072 | 1.149 |
| Valid N (listwise) | 380 |  |  |  |  |  |

**Table 6: Form/Modality Descriptive Statistics**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Descriptive Statistics** | | | | | | |
|  | N | Minimum | Maximum | Mean | Std. Deviation | Variance |
| I would organize a public action against the firm in the case of a dispute. | 380 | 1 | 5 | 3.57 | .906 | .821 |
| I tend to express my experiences through blogs. | 380 | 1 | 5 | 3.08 | .999 | .999 |
| I actively participate in firm-organized charity events, donating money and time. | 380 | 1 | 5 | 2.82 | 1.084 | 1.174 |
| I generally donate through charity events but do not have the time to participate in them. | 380 | 1 | 5 | 2.81 | 1.092 | 1.192 |
| I tend to complain about the app/firm on social media forums. | 380 | 1 | 5 | 2.91 | 1.107 | 1.225 |
| Valid N (listwise) | 380 |  |  |  |  |  |

**Table 7: Choice of Channel Descriptive Statistics**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Descriptive Statistics** | | | | | | |
|  | N | Minimum | Maximum | Mean | Std. Deviation | Variance |
| with other customers in-person | 380 | 1 | 5 | 2.79 | 1.101 | 1.213 |
| with other customers via the Internet (social media or website). | 380 | 1 | 5 | 3.46 | 1.030 | 1.061 |
| with other customers via phone, mail, or e-mail. | 380 | 1 | 5 | 3.33 | .993 | .986 |
| with the company in-person customer to firm. | 380 | 1 | 5 | 3.19 | .976 | .952 |
| with the company via the Internet (social-media or website). | 380 | 1 | 5 | 3.30 | 1.030 | 1.060 |
| with the company via phone/mail/e-mail. | 380 | 1 | 5 | 3.20 | 1.094 | 1.196 |
| Valid N (listwise) | 380 |  |  |  |  |  |

**Table 8: Scope Descriptive Statistics**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Descriptive Statistics** | | | | | | |
|  | N | Minimum | Maximum | Mean | Std. Deviation | Variance |
| My product-related expressions and actions help my company | 380 | 1 | 5 | 3.15 | 1.053 | 1.109 |
| I provide feedback about my app experiences to the firm. | 380 | 1 | 5 | 3.21 | 1.092 | 1.192 |
| I provide suggestions for improving the performance of the app. | 380 | 1 | 5 | 3.23 | 1.074 | 1.153 |
| I provide feedback/suggestions for developing new service offerings for my app. | 380 | 1 | 5 | 3.35 | 1.119 | 1.253 |
| Valid N (listwise) | 380 |  |  |  |  |  |

**Table 9: Moral Identity Descriptive Statistics**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Descriptive Statistics** | | | | | | |
|  | N | Minimum | Maximum | Mean | Std. Deviation | Variance |
| I want to warn others of bad financial applications | 380 | 1 | 5 | 3.29 | 1.076 | 1.158 |
| I want to save others from having the same negative experiences as me. | 380 | 1 | 5 | 3.43 | 1.096 | 1.201 |
| I want to help others with my own positive experiences. | 380 | 1 | 5 | 3.83 | .951 | .904 |
| I want to allow others to install /use the right financial application. | 380 | 1 | 5 | 3.81 | .973 | .947 |
| Valid N (listwise) | 380 |  |  |  |  |  |

**Table 10: Perceived Benefits Descriptive Statistics**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Descriptive Statistics** | | | | | | |
|  | N | Minimum | Maximum | Mean | Std. Deviation | Variance |
| I manage to doFinTech transactions in the least amount of time. | 380 | 1 | 5 | 3.68 | 1.015 | 1.031 |
| It has useful features. | 380 | 1 | 5 | 3.83 | .979 | .958 |
| This financial application gives me better deals. | 380 | 1 | 5 | 3.52 | 1.039 | 1.079 |
| The app has exclusive time-bound offers | 380 | 1 | 5 | 3.53 | .975 | .952 |
| While shopping through the app, I find what I'm looking for quickly. | 380 | 1 | 5 | 3.60 | .995 | .990 |
| I expend little effort to do transactions through FinTech compared to other channels. | 380 | 1 | 5 | 3.56 | 1.042 | 1.087 |
| Valid N (listwise) | 380 |  |  |  |  |  |

**Table 11: Perceived Costs Descriptive Statistics**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Descriptive Statistics** | | | | | | |
|  | N | Minimum | Maximum | Mean | Std. Deviation | Variance |
| App installation cost is not very high | 380 | 1 | 5 | 3.66 | 1.202 | 1.445 |
| Transaction processing cost with FinTech applications is high. | 380 | 1 | 5 | 3.12 | 1.112 | 1.237 |
| These applications help me save money. | 380 | 1 | 5 | 3.36 | 1.123 | 1.260 |
| Valid N (listwise) | 380 |  |  |  |  |  |

**Table 12: Self-Concept Descriptive Statistics**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Descriptive Statistics** | | | | | | |
|  | N | Minimum | Maximum | Mean | Std. Deviation | Variance |
| I identify with what my company or app stands for. | 380 | 1 | 5 | 3.22 | .955 | .911 |
| I feel a sense of belonging concerning my company. | 380 | 1 | 5 | 3.17 | 1.005 | 1.009 |
| I bring up things I have seen on this app in conversations with other people | 380 | 1 | 5 | 3.43 | .981 | .963 |
| When I talk about this brand, I usually say ‘we’ rather than they. | 380 | 1 | 5 | 2.93 | 1.109 | 1.230 |
| This brand’s successes are my successes. | 380 | 1 | 5 | 2.89 | 1.125 | 1.265 |
| Valid N (listwise) | 380 |  |  |  |  |  |